autogluon_all

October 7, 2023

[30]:

```
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0]
    return X



def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")

    # # print start and end dates for X_train_estimated
    # print(f"X_train_estimated start date: {X_train_estimated.index.min()}")
    # print(f"X_train_estimated end date: {X_train_estimated.index.max()}")


    X_train_observed["estimated_diff_hours"] = 0
    X_train_observed["is_estimated"] = False
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
 ↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
```

```
    X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

    X_train_estimated["is_estimated"] = True
    X_test["is_estimated"] = True

    X_train_estimated["estimated_diff_hours"] =␣
 ↪X_train_estimated["estimated_diff_hours"].astype('int64')
    # the filled once will get dropped later anyways, when we drop y nans
    X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).
 ↪astype('int64')


    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
 ↪convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)

    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)

    X_train = pd.concat([X_train_observed, X_train_estimated], axis=0)#,␣
 ↪X_train_estimated, X_train_estimated, X_train_estimated, X_train_estimated],␣
 ↪axis=0)
    # weight the estimated X_train higher



    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)
```

```
    X_train = pd.merge(X_train, y_train, how="outer", left_index=True,␣
 ↪right_index=True)

    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Processing location B…
Processing location C…
```

1 Feature enginering

[31]:
```
# temporary
X_train["hour"] = X_train.index.hour
X_train["weekday"] = X_train.index.weekday
X_train["is_weekend"] = X_train["weekday"].isin([5, 6])
X_train["month"] = X_train.index.month
X_train["year"] = X_train.index.year

X_test["hour"] = X_test.index.hour
X_test["weekday"] = X_test.index.weekday
X_test["is_weekend"] = X_test["weekday"].isin([5, 6])
X_test["month"] = X_test.index.month
X_test["year"] = X_test.index.year


to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.dropna(subset=['y'], inplace=True)
X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

[32]:
```
import autogluon.eda.auto as auto
auto.dataset_overview(train_data=X_train, test_data=X_test, label="y",␣
↪sample=None)
```

train_data dataset summary

```
                         count  unique   top   freq            mean  \
absolute_humidity_2m:gm3 92951     165                     6.017608
air_density_2m:kgm3      92951     293                     1.255435
ceiling_height_agl:m     72276   40993                  2802.588135
clear_sky_energy_1h:J    92951   48602                515154.09375
clear_sky_rad:W          92951    7815                   143.101379
cloud_base_agl:m         84404   34862                  1692.934692
dew_or_rime:idx          92951       3                     0.007025
dew_point_2m:K           92951     436                   275.237762
diffuse_rad:W            92951    2870                    39.495815
diffuse_rad_1h:J         92951   48553                142180.03125
direct_rad:W             92951    5296                    50.205021
direct_rad_1h:J          92951   41885                 180740.1875
effective_cloud_cover:p  92951    1001                    67.013519
elevation:m              92951       3                    11.401738
estimated_diff_hours     92951      26                     3.143516
fresh_snow_12h:cm        92951     125                     0.116175
```

fresh_snow_1h:cm	92951	39			0.00963
fresh_snow_24h:cm	92951	161			0.229894
fresh_snow_3h:cm	92951	70			0.029001
fresh_snow_6h:cm	92951	96			0.058069
hour	93024	24			11.501462
is_day:idx	92951	2			0.483341
is_estimated	92951	2	False	82026	
is_in_shadow:idx	92951	2			0.565384
location	93024	3	A	34085	
month	93024	12			6.290484
msl_pressure:hPa	92951	874			1009.502563
precip_5min:mm	92951	64			0.005674
precip_type_5min:idx	92951	7			0.083259
pressure_100m:hPa	92951	888			995.81897
pressure_50m:hPa	92951	897			1001.949646
prob_rime:p	92951	700			0.756834
rain_water:kgm2	92951	11			0.009677
relative_humidity_1000hPa:p	92951	788			73.669556
sfc_pressure:hPa	92951	902			1008.107849
snow_depth:cm	92951	165			0.193203
snow_melt_10min:mm	92951	19			0.000275
snow_water:kgm2	92951	42			0.090324
sun_azimuth:d	92951	69692			182.386337
sun_elevation:d	92951	49376			-1.207574
super_cooled_liquid_water:kgm2	92951	15			0.056944
t_1000hPa:K	92951	447			279.431061
total_cloud_cover:p	92951	1001			73.604263
visibility:m	92951	85686			33027.933594
weekday	93024	7			3.00215
wind_speed_10m:ms	92951	119			3.037911
wind_speed_u_10m:ms	92951	188			0.662565
wind_speed_v_10m:ms	92951	167			0.6824
wind_speed_w_1000hPa:ms	92951	3			-0.000016
y	93024	12430			287.019652
year	93024	6			2020.69495

	std	min	25% \
absolute_humidity_2m:gm3	2.714546	0.5	4.0
air_density_2m:kgm3	0.036608	1.139	1.23
ceiling_height_agl:m	2521.408447	27.799999	1037.099976
clear_sky_energy_1h:J	820525.5	0.0	0.0
clear_sky_rad:W	228.507324	0.0	0.0
cloud_base_agl:m	1790.963745	27.4	572.200012
dew_or_rime:idx	0.246032	-1.0	0.0
dew_point_2m:K	6.83461	247.300003	270.700012
diffuse_rad:W	60.647518	0.0	0.0
diffuse_rad_1h:J	215907.21875	0.0	0.0
direct_rad:W	112.946068	0.0	0.0

direct_rad_1h:J	401735.03125	0.0	0.0
effective_cloud_cover:p	35.044811	0.0	41.299999
elevation:m	7.877236	6.0	6.0
estimated_diff_hours	8.935328	0.0	0.0
fresh_snow_12h:cm	0.780374	0.0	0.0
fresh_snow_1h:cm	0.112621	0.0	0.0
fresh_snow_24h:cm	1.218249	0.0	0.0
fresh_snow_3h:cm	0.28067	0.0	0.0
fresh_snow_6h:cm	0.481389	0.0	0.0
hour	6.92022	0.0	6.0
is_day:idx	0.499725	0.0	0.0
is_estimated			
is_in_shadow:idx	0.495709	0.0	0.0
location			
month	3.587269	1.0	3.0
msl_pressure:hPa	13.089046	944.299988	1001.400024
precip_5min:mm	0.033511	0.0	0.0
precip_type_5min:idx	0.384904	0.0	0.0
pressure_100m:hPa	13.008334	929.799988	987.799988
pressure_50m:hPa	13.067102	935.599976	993.900024
prob_rime:p	5.434649	0.0	0.0
rain_water:kgm2	0.042968	0.0	0.0
relative_humidity_1000hPa:p	14.328553	19.5	64.199997
sfc_pressure:hPa	13.128181	941.400024	1000.0
snow_depth:cm	1.254293	0.0	0.0
snow_melt_10min:mm	0.004312	-0.0	-0.0
snow_water:kgm2	0.250991	0.0	0.0
sun_azimuth:d	102.913605	0.008	92.794006
sun_elevation:d	24.010485	-49.979	-18.511
super_cooled_liquid_water:kgm2	0.111482	0.0	0.0
t_1000hPa:K	6.520342	257.899994	274.899994
total_cloud_cover:p	34.993042	0.0	51.700001
visibility:m	18319.150391	130.600006	15798.950195
weekday	2.000961	0.0	1.0
wind_speed_10m:ms	1.778505	0.0	1.7
wind_speed_u_10m:ms	2.808995	-7.3	-1.4
wind_speed_v_10m:ms	1.896996	-9.3	-0.6
wind_speed_w_1000hPa:ms	0.006502	-0.1	0.0
y	766.407785	-0.0	0.0
year	1.187172	2018.0	2020.0

	50%	75%	max \
absolute_humidity_2m:gm3	5.4	7.8	17.5
air_density_2m:kgm3	1.255	1.279	1.441
ceiling_height_agl:m	1803.25	3814.824951	12431.299805
clear_sky_energy_1h:J	4544.899902	778247.25	3006697.25
clear_sky_rad:W	0.0	220.949997	835.299988
cloud_base_agl:m	1128.550049	2016.699951	11688.900391

```
dew_or_rime:idx                      0.0          0.0          1.0
dew_point_2m:K                     275.0        280.5   293.799988
diffuse_rad:W                        0.0         66.0   340.100006
diffuse_rad_1h:J             9951.700195    236502.75  1182265.375
direct_rad:W                         0.0         29.0   684.299988
direct_rad_1h:J                      0.0    113366.25    2445897.0
effective_cloud_cover:p        80.800003    99.300003        100.0
elevation:m                          7.0         24.0         24.0
estimated_diff_hours                 0.0          0.0         39.0
fresh_snow_12h:cm                    0.0          0.0    37.400002
fresh_snow_1h:cm                     0.0          0.0          7.1
fresh_snow_24h:cm                    0.0          0.0    37.400002
fresh_snow_3h:cm                     0.0          0.0         20.6
fresh_snow_6h:cm                     0.0          0.0         34.0
hour                                12.0         17.0         23.0
is_day:idx                           0.0          1.0          1.0
is_estimated
is_in_shadow:idx                     1.0          1.0          1.0
location
month                                6.0         10.0         12.0
msl_pressure:hPa             1010.299988  1018.599976  1044.099976
precip_5min:mm                       0.0          0.0         1.38
precip_type_5min:idx                 0.0          0.0          6.0
pressure_100m:hPa             996.799988  1004.900024  1030.900024
pressure_50m:hPa             1002.900024  1011.099976  1037.300049
prob_rime:p                          0.0          0.0    97.199997
rain_water:kgm2                      0.0          0.0          1.4
relative_humidity_1000hPa:p         76.0    85.099998        100.0
sfc_pressure:hPa                  1009.0  1017.200012  1043.800049
snow_depth:cm                        0.0          0.0    18.299999
snow_melt_10min:mm                   0.0         -0.0         0.18
snow_water:kgm2                      0.0          0.1          6.9
sun_azimuth:d                 179.526001   271.503479   359.997009
sun_elevation:d                    -0.99       15.538    49.917999
super_cooled_liquid_water:kgm2       0.0          0.1          1.4
t_1000hPa:K                   278.700012   283.899994   303.299988
total_cloud_cover:p            94.800003        100.0        100.0
visibility:m                37350.300781 48679.550781 76737.796875
weekday                              3.0          5.0          6.0
wind_speed_10m:ms                    2.7          4.1         15.2
wind_speed_u_10m:ms                  0.3          2.5         12.2
wind_speed_v_10m:ms                  0.7          1.9          9.0
wind_speed_w_1000hPa:ms              0.0          0.0          0.1
y                                    0.0       172.92      5733.42
year                              2021.0       2022.0       2023.0

                                 dtypes missing_count missing_ratio raw_type  \
absolute_humidity_2m:gm3        float32            73      0.000785    float
```

air_density_2m:kgm3	float32	73	0.000785	float
ceiling_height_agl:m	float32	20748	0.223039	float
clear_sky_energy_1h:J	float32	73	0.000785	float
clear_sky_rad:W	float32	73	0.000785	float
cloud_base_agl:m	float32	8620	0.092664	float
dew_or_rime:idx	float32	73	0.000785	float
dew_point_2m:K	float32	73	0.000785	float
diffuse_rad:W	float32	73	0.000785	float
diffuse_rad_1h:J	float32	73	0.000785	float
direct_rad:W	float32	73	0.000785	float
direct_rad_1h:J	float32	73	0.000785	float
effective_cloud_cover:p	float32	73	0.000785	float
elevation:m	float32	73	0.000785	float
estimated_diff_hours	float64	73	0.000785	float
fresh_snow_12h:cm	float32	73	0.000785	float
fresh_snow_1h:cm	float32	73	0.000785	float
fresh_snow_24h:cm	float32	73	0.000785	float
fresh_snow_3h:cm	float32	73	0.000785	float
fresh_snow_6h:cm	float32	73	0.000785	float
hour	int64			int
is_day:idx	float32	73	0.000785	float
is_estimated	object	73	0.000785	object
is_in_shadow:idx	float32	73	0.000785	float
location	object			object
month	int64			int
msl_pressure:hPa	float32	73	0.000785	float
precip_5min:mm	float32	73	0.000785	float
precip_type_5min:idx	float32	73	0.000785	float
pressure_100m:hPa	float32	73	0.000785	float
pressure_50m:hPa	float32	73	0.000785	float
prob_rime:p	float32	73	0.000785	float
rain_water:kgm2	float32	73	0.000785	float
relative_humidity_1000hPa:p	float32	73	0.000785	float
sfc_pressure:hPa	float32	73	0.000785	float
snow_depth:cm	float32	73	0.000785	float
snow_melt_10min:mm	float32	73	0.000785	float
snow_water:kgm2	float32	73	0.000785	float
sun_azimuth:d	float32	73	0.000785	float
sun_elevation:d	float32	73	0.000785	float
super_cooled_liquid_water:kgm2	float32	73	0.000785	float
t_1000hPa:K	float32	73	0.000785	float
total_cloud_cover:p	float32	73	0.000785	float
visibility:m	float32	73	0.000785	float
weekday	int64			int
wind_speed_10m:ms	float32	73	0.000785	float
wind_speed_u_10m:ms	float32	73	0.000785	float
wind_speed_v_10m:ms	float32	73	0.000785	float
wind_speed_w_1000hPa:ms	float32	73	0.000785	float

```
y                              float64                                   float
year                             int64                                     int

                              variable_type special_types
absolute_humidity_2m:gm3            numeric
air_density_2m:kgm3                 numeric
ceiling_height_agl:m                numeric
clear_sky_energy_1h:J               numeric
clear_sky_rad:W                     numeric
cloud_base_agl:m                    numeric
dew_or_rime:idx                    category
dew_point_2m:K                      numeric
diffuse_rad:W                       numeric
diffuse_rad_1h:J                    numeric
direct_rad:W                        numeric
direct_rad_1h:J                     numeric
effective_cloud_cover:p             numeric
elevation:m                        category
estimated_diff_hours                numeric
fresh_snow_12h:cm                   numeric
fresh_snow_1h:cm                    numeric
fresh_snow_24h:cm                   numeric
fresh_snow_3h:cm                    numeric
fresh_snow_6h:cm                    numeric
hour                                numeric
is_day:idx                         category
is_estimated                       category
is_in_shadow:idx                   category
location                           category
month                              category
msl_pressure:hPa                    numeric
precip_5min:mm                      numeric
precip_type_5min:idx               category
pressure_100m:hPa                   numeric
pressure_50m:hPa                    numeric
prob_rime:p                         numeric
rain_water:kgm2                    category
relative_humidity_1000hPa:p         numeric
sfc_pressure:hPa                    numeric
snow_depth:cm                       numeric
snow_melt_10min:mm                 category
snow_water:kgm2                     numeric
sun_azimuth:d                       numeric
sun_elevation:d                     numeric
super_cooled_liquid_water:kgm2     category
t_1000hPa:K                         numeric
total_cloud_cover:p                 numeric
visibility:m                        numeric
```

weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
y	numeric
year	category

test_data dataset summary

	count	unique	top	freq	mean	\
absolute_humidity_2m:gm3	2160	106			8.206482	
air_density_2m:kgm3	2160	153			1.232807	
ceiling_height_agl:m	1473	1391			2938.389648	
clear_sky_energy_1h:J	2160	1807			1227746.75	
clear_sky_rad:W	2160	1044			341.056641	
cloud_base_agl:m	1879	1771			1797.160156	
dew_or_rime:idx	2160	3			0.040741	
dew_point_2m:K	2160	202			280.783203	
diffuse_rad:W	2160	985			84.915688	
diffuse_rad_1h:J	2160	1806			305696.5	
direct_rad:W	2160	916			114.279816	
direct_rad_1h:J	2160	1634			411408.875	
effective_cloud_cover:p	2160	590			64.113792	
elevation:m	2160	3			12.333333	
estimated_diff_hours	2160	24			27.5	
fresh_snow_12h:cm	2160	2			0.000185	
fresh_snow_1h:cm	2160	2			0.000185	
fresh_snow_24h:cm	2160	2			0.000185	
fresh_snow_3h:cm	2160	2			0.000185	
fresh_snow_6h:cm	2160	2			0.000185	
hour	2160	24			11.5	
is_day:idx	2160	2			0.795833	
is_estimated	2160	1	True	2160		
is_in_shadow:idx	2160	2			0.24537	
location	2160	3	A	720		
month	2160	3			5.666667	
msl_pressure:hPa	2160	321			1016.805786	
precip_5min:mm	2160	27			0.00775	
precip_type_5min:idx	2160	3			0.065741	
pressure_100m:hPa	2160	359			1002.970825	
pressure_50m:hPa	2160	356			1009.007202	
prob_rime:p	2160	3			0.01588	
rain_water:kgm2	2160	8			0.013056	
relative_humidity_1000hPa:p	2160	538			70.920792	
sfc_pressure:hPa	2160	363			1015.070374	
snow_depth:cm	2160	1			0.0	
snow_melt_10min:mm	2160	1			0.0	
snow_water:kgm2	2160	16			0.060972	

sun_azimuth:d	2160	1830	183.166199
sun_elevation:d	2160	1623	20.292332
super_cooled_liquid_water:kgm2	2160	7	0.065463
t_1000hPa:K	2160	254	284.737732
total_cloud_cover:p	2160	553	69.298981
visibility:m	2160	2155	33304.636719
weekday	2160	7	3.233333
wind_speed_10m:ms	2160	83	2.946759
wind_speed_u_10m:ms	2160	123	1.650694
wind_speed_v_10m:ms	2160	80	-0.187176
wind_speed_w_1000hPa:ms	2160	2	0.000324
year	2160	1	2023.0

	std	min	25% \
absolute_humidity_2m:gm3	2.201396	3.2	6.6
air_density_2m:kgm3	0.032116	1.142	1.209
ceiling_height_agl:m	2913.641113	30.6	891.799988
clear_sky_energy_1h:J	1104468.625	0.0	64338.124023
clear_sky_rad:W	307.729095	0.0	13.65
cloud_base_agl:m	2046.394409	29.799999	486.899994
dew_or_rime:idx	0.202365	-1.0	0.0
dew_point_2m:K	4.378817	268.0	277.899994
diffuse_rad:W	78.422508	0.0	6.925
diffuse_rad_1h:J	278146.25	0.0	36756.901367
direct_rad:W	171.838226	0.0	0.0
direct_rad_1h:J	611480.125	0.0	86.575001
effective_cloud_cover:p	37.947498	0.0	30.700001
elevation:m	8.261587	6.0	6.0
estimated_diff_hours	6.923789	16.0	21.75
fresh_snow_12h:cm	0.008607	0.0	0.0
fresh_snow_1h:cm	0.008607	0.0	0.0
fresh_snow_24h:cm	0.008607	0.0	0.0
fresh_snow_3h:cm	0.008607	0.0	0.0
fresh_snow_6h:cm	0.008607	0.0	0.0
hour	6.923789	0.0	5.75
is_day:idx	0.403185	0.0	1.0
is_estimated			
is_in_shadow:idx	0.430406	0.0	0.0
location			
month	0.596423	5.0	5.0
msl_pressure:hPa	9.728754	986.099976	1011.5
precip_5min:mm	0.033776	0.0	0.0
precip_type_5min:idx	0.249747	0.0	0.0
pressure_100m:hPa	9.644145	971.799988	997.799988
pressure_50m:hPa	9.74076	977.700012	1003.799988
prob_rime:p	0.551282	0.0	0.0
rain_water:kgm2	0.055256	0.0	0.0
relative_humidity_1000hPa:p	15.725973	23.9	60.275

sfc_pressure:hPa	9.840412	983.5	1009.799988
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	-0.0	-0.0
snow_water:kgm2	0.219562	0.0	0.0
sun_azimuth:d	109.193207	8.27	85.359253
sun_elevation:d	18.681047	-11.617	1.96475
super_cooled_liquid_water:kgm2	0.115824	0.0	0.0
t_1000hPa:K	5.839595	273.700012	279.799988
total_cloud_cover:p	38.41222	0.0	32.799999
visibility:m	15624.633789	874.400024	19635.100098
weekday	2.186573	0.0	1.0
wind_speed_10m:ms	1.733865	0.0	1.5
wind_speed_u_10m:ms	2.578466	-4.3	-0.2
wind_speed_v_10m:ms	1.50826	-4.4	-1.3
wind_speed_w_1000hPa:ms	0.005685	-0.0	0.0
year	0.0	2023.0	2023.0

	50%	75%	max \
absolute_humidity_2m:gm3	8.0	10.0	14.2
air_density_2m:kgm3	1.238	1.26	1.301
ceiling_height_agl:m	1553.900024	4021.300049	11468.0
clear_sky_energy_1h:J	1056303.125	2372037.5	3005707.0
clear_sky_rad:W	273.849991	646.874985	835.099976
cloud_base_agl:m	997.799988	2298.300049	11467.799805
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	281.0	284.299988	290.200012
diffuse_rad:W	73.700001	135.600006	312.600006
diffuse_rad_1h:J	272526.046875	488256.03125	1086246.25
direct_rad:W	16.200001	180.399994	668.0
direct_rad_1h:J	60416.199219	686746.859375	2403444.25
effective_cloud_cover:p	77.75	100.0	100.0
elevation:m	7.0	24.0	24.0
estimated_diff_hours	27.5	33.25	39.0
fresh_snow_12h:cm	0.0	0.0	0.4
fresh_snow_1h:cm	0.0	0.0	0.4
fresh_snow_24h:cm	0.0	0.0	0.4
fresh_snow_3h:cm	0.0	0.0	0.4
fresh_snow_6h:cm	0.0	0.0	0.4
hour	11.5	17.25	23.0
is_day:idx	1.0	1.0	1.0
is_estimated			
is_in_shadow:idx	0.0	0.0	1.0
location			
month	6.0	6.0	7.0
msl_pressure:hPa	1020.599976	1023.799988	1029.599976
precip_5min:mm	0.0	0.0	0.34
precip_type_5min:idx	0.0	0.0	2.0
pressure_100m:hPa	1006.25	1010.099976	1016.400024

pressure_50m:hPa	1012.299988	1016.200012	1022.5
prob_rime:p	0.0	0.0	23.0
rain_water:kgm2	0.0	0.0	0.7
relative_humidity_1000hPa:p	73.900002	83.699997	98.900002
sfc_pressure:hPa	1018.299988	1022.299988	1028.699951
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	0.0	0.0
snow_water:kgm2	0.0	0.0	3.4
sun_azimuth:d	184.236	279.576248	356.984009
sun_elevation:d	18.54	38.102499	49.902
super_cooled_liquid_water:kgm2	0.0	0.1	0.6
t_1000hPa:K	284.799988	288.299988	302.200012
total_cloud_cover:p	95.300003	100.0	100.0
visibility:m	37623.050781	45378.099609	63863.800781
weekday	3.0	5.0	6.0
wind_speed_10m:ms	2.7	4.0	8.8
wind_speed_u_10m:ms	1.6	3.525	8.8
wind_speed_v_10m:ms	-0.3	0.8	4.0
wind_speed_w_1000hPa:ms	0.0	0.0	0.1
year	2023.0	2023.0	2023.0

	dtypes	missing_count	missing_ratio	raw_type \
absolute_humidity_2m:gm3	float32			float
air_density_2m:kgm3	float32			float
ceiling_height_agl:m	float32	687	0.318056	float
clear_sky_energy_1h:J	float32			float
clear_sky_rad:W	float32			float
cloud_base_agl:m	float32	281	0.130093	float
dew_or_rime:idx	float32			float
dew_point_2m:K	float32			float
diffuse_rad:W	float32			float
diffuse_rad_1h:J	float32			float
direct_rad:W	float32			float
direct_rad_1h:J	float32			float
effective_cloud_cover:p	float32			float
elevation:m	float32			float
estimated_diff_hours	int64			int
fresh_snow_12h:cm	float32			float
fresh_snow_1h:cm	float32			float
fresh_snow_24h:cm	float32			float
fresh_snow_3h:cm	float32			float
fresh_snow_6h:cm	float32			float
hour	int64			int
is_day:idx	float32			float
is_estimated	bool			bool
is_in_shadow:idx	float32			float
location	object			object
month	int64			int

```
msl_pressure:hPa              float32                                   float
precip_5min:mm                float32                                   float
precip_type_5min:idx          float32                                   float
pressure_100m:hPa             float32                                   float
pressure_50m:hPa              float32                                   float
prob_rime:p                   float32                                   float
rain_water:kgm2               float32                                   float
relative_humidity_1000hPa:p   float32                                   float
sfc_pressure:hPa              float32                                   float
snow_depth:cm                 float32                                   float
snow_melt_10min:mm            float32                                   float
snow_water:kgm2               float32                                   float
sun_azimuth:d                 float32                                   float
sun_elevation:d               float32                                   float
super_cooled_liquid_water:kgm2  float32                                 float
t_1000hPa:K                   float32                                   float
total_cloud_cover:p           float32                                   float
visibility:m                  float32                                   float
weekday                         int64                                     int
wind_speed_10m:ms             float32                                   float
wind_speed_u_10m:ms           float32                                   float
wind_speed_v_10m:ms           float32                                   float
wind_speed_w_1000hPa:ms       float32                                   float
year                            int64                                     int
```

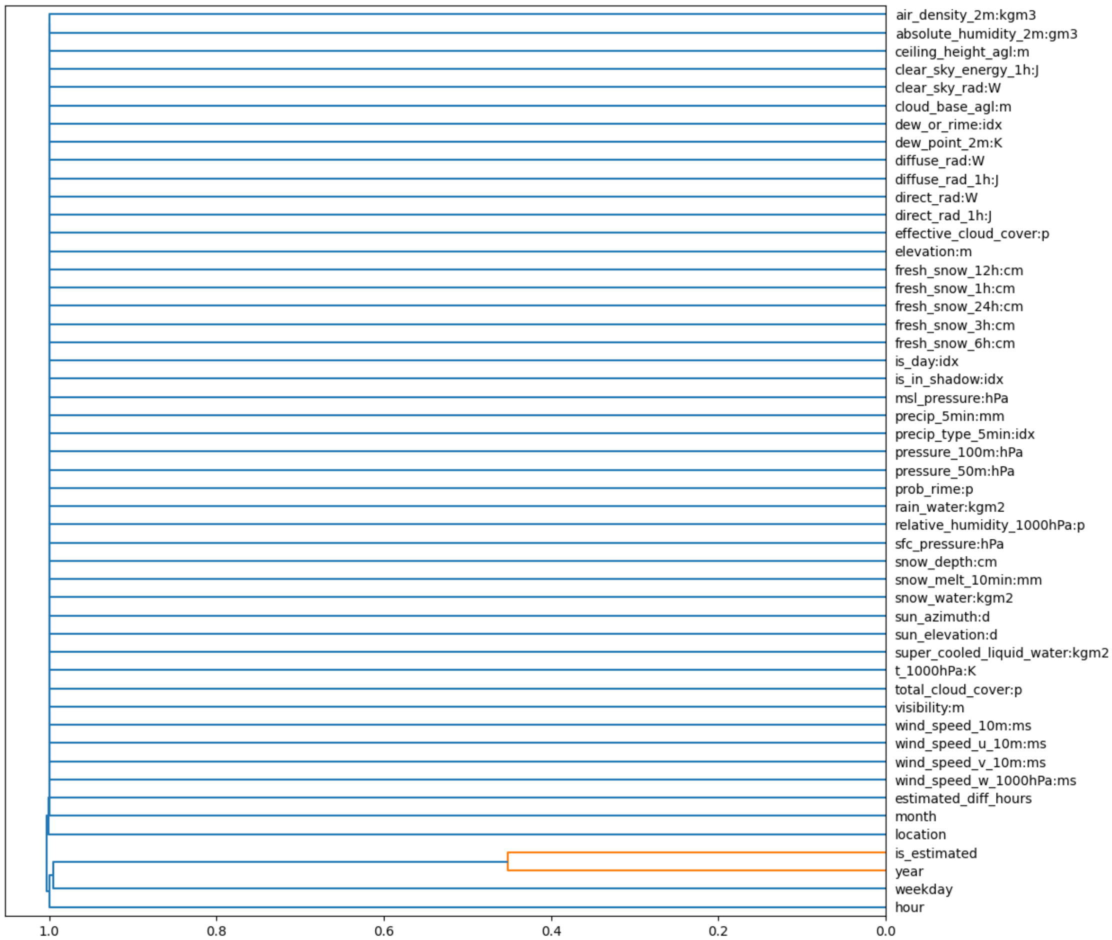
```
                              variable_type special_types
absolute_humidity_2m:gm3            numeric
air_density_2m:kgm3                 numeric
ceiling_height_agl:m                numeric
clear_sky_energy_1h:J               numeric
clear_sky_rad:W                     numeric
cloud_base_agl:m                    numeric
dew_or_rime:idx                    category
dew_point_2m:K                      numeric
diffuse_rad:W                       numeric
diffuse_rad_1h:J                    numeric
direct_rad:W                        numeric
direct_rad_1h:J                     numeric
effective_cloud_cover:p             numeric
elevation:m                        category
estimated_diff_hours                numeric
fresh_snow_12h:cm                  category
fresh_snow_1h:cm                   category
fresh_snow_24h:cm                  category
fresh_snow_3h:cm                   category
fresh_snow_6h:cm                   category
hour                                numeric
is_day:idx                         category
```

is_estimated	category
is_in_shadow:idx	category
location	category
month	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
prob_rime:p	category
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sfc_pressure:hPa	numeric
snow_depth:cm	category
snow_melt_10min:mm	category
snow_water:kgm2	category
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	category
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
year	category

Types warnings summary

	train_data	test_data	warnings
estimated_diff_hours	float	int	warning
is_estimated	object	bool	warning
y	float	--	warning

1.0.1 Feature Distance

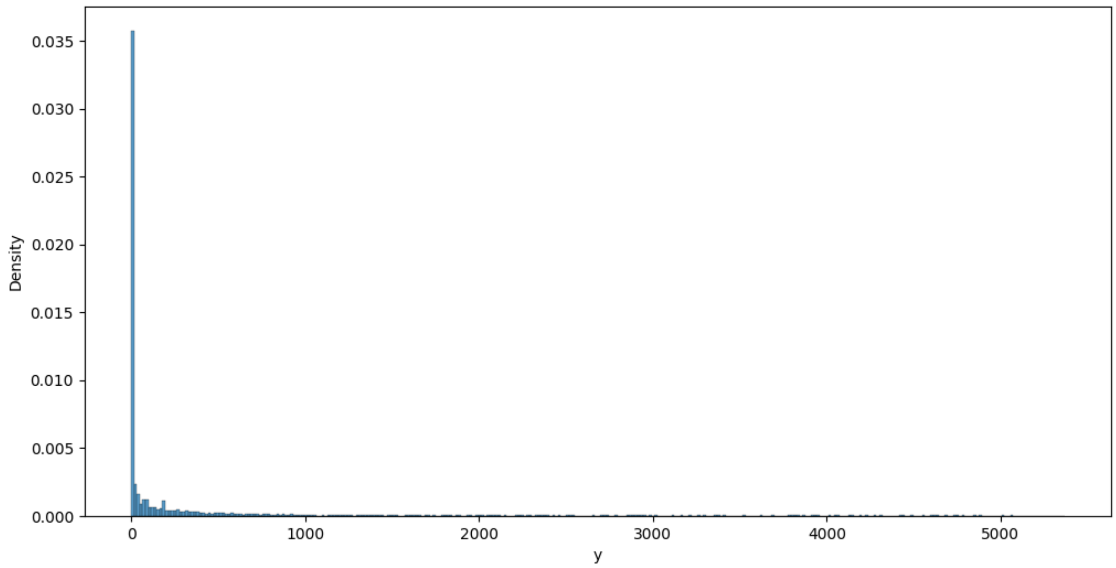


[33]:
```python
auto.target_analysis(train_data=X_train, label="y")#, sample=None)
```

1.1 Target variable analysis

```
   count       mean        std  min  25%  50%    75%      max   dtypes  \
y  10000  295.26029  787.46272 -0.0  0.0  0.0  176.4  5365.36  float64

   unique missing_count missing_ratio raw_type special_types
y    2539                                 float
```

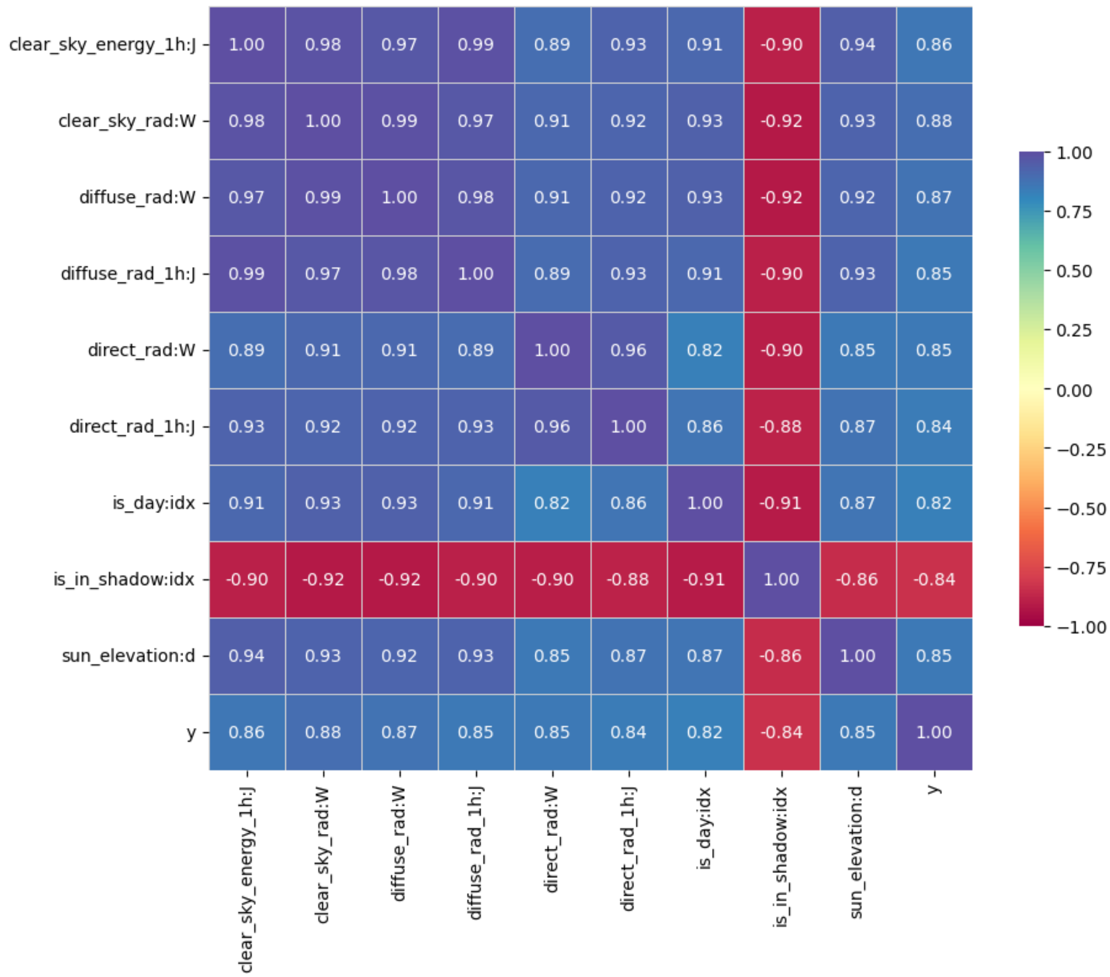


1.1.1 Distribution fits for target variable

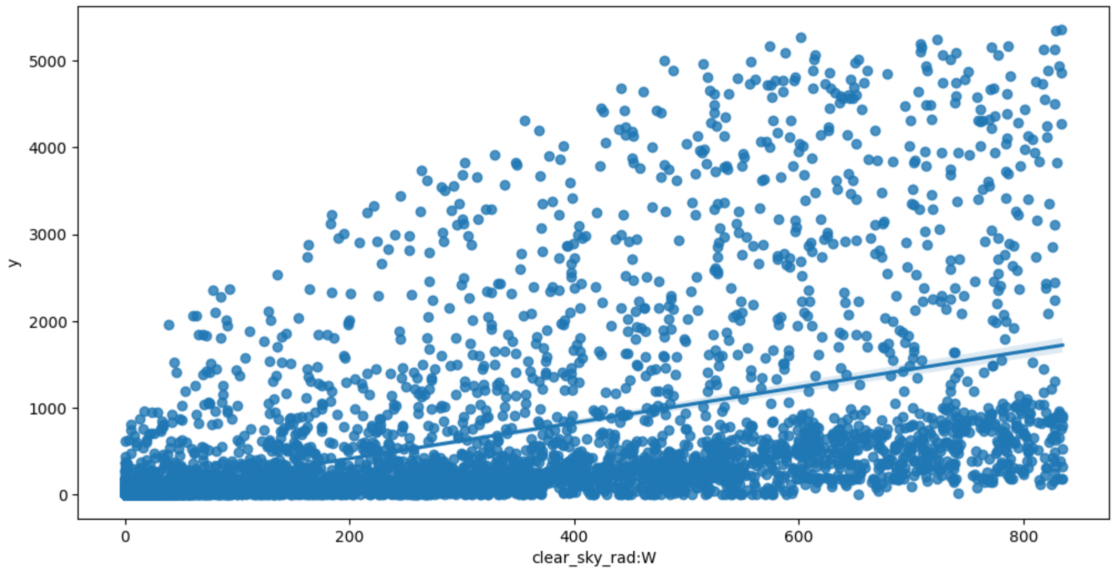
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

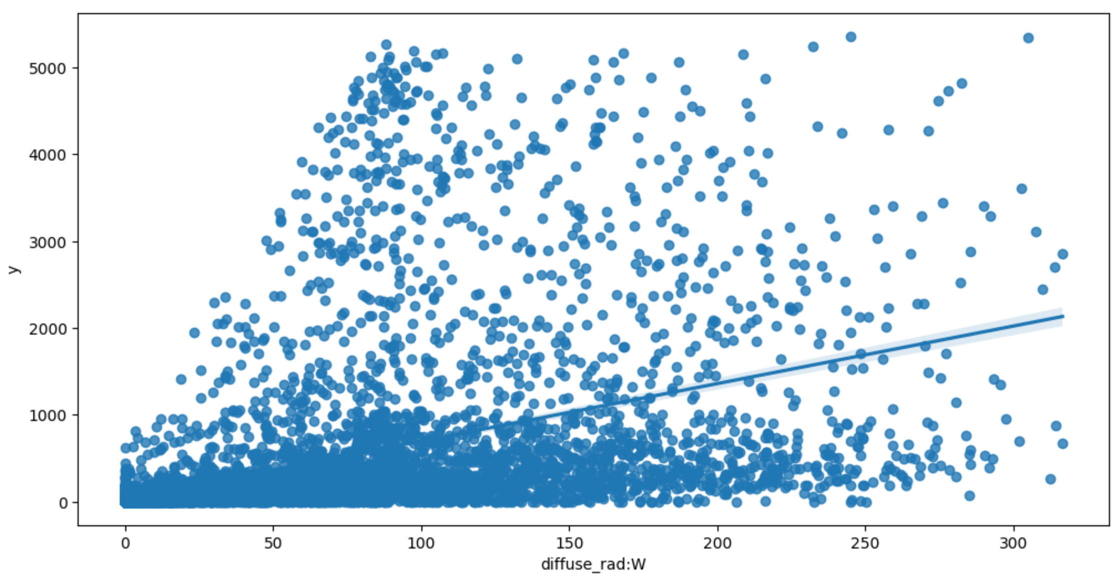
`train_data` - `spearman` correlation matrix; focus: absolute correlation for `y` >= `0.5` (sample size: 10000)



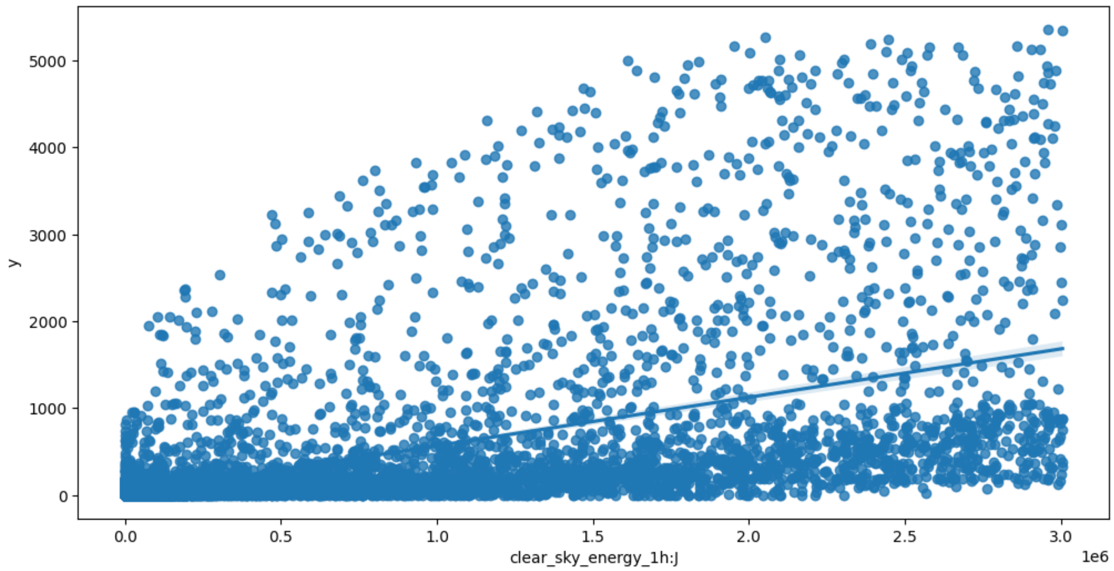
Feature interaction between `clear_sky_rad:W`/`y` in `train_data` (sample size: 10000)



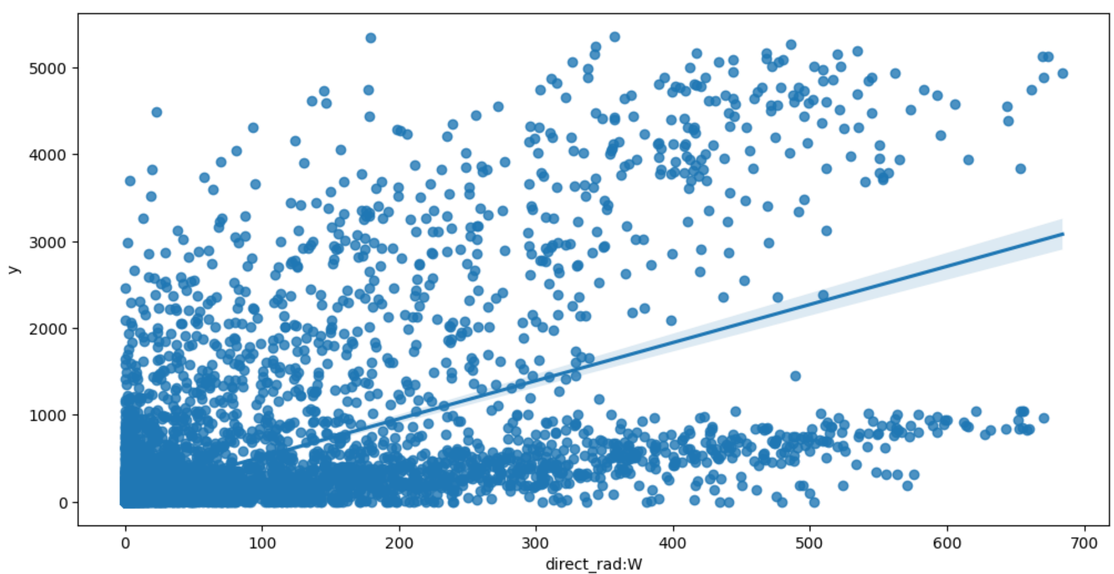
Feature interaction between `diffuse_rad:W/y` in `train_data` (sample size: 10000)



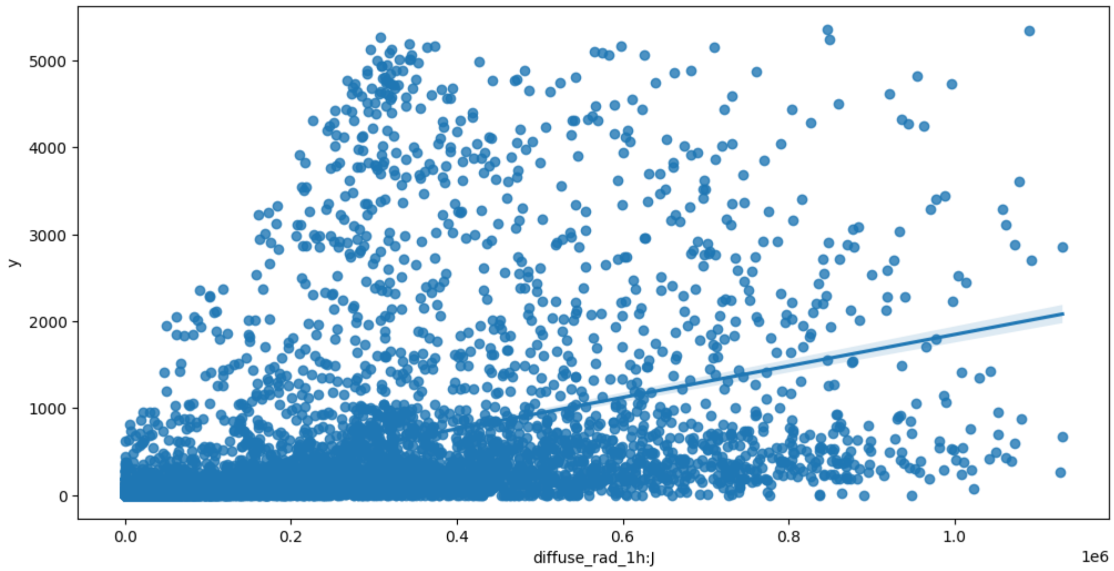
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data` (sample size: 10000)



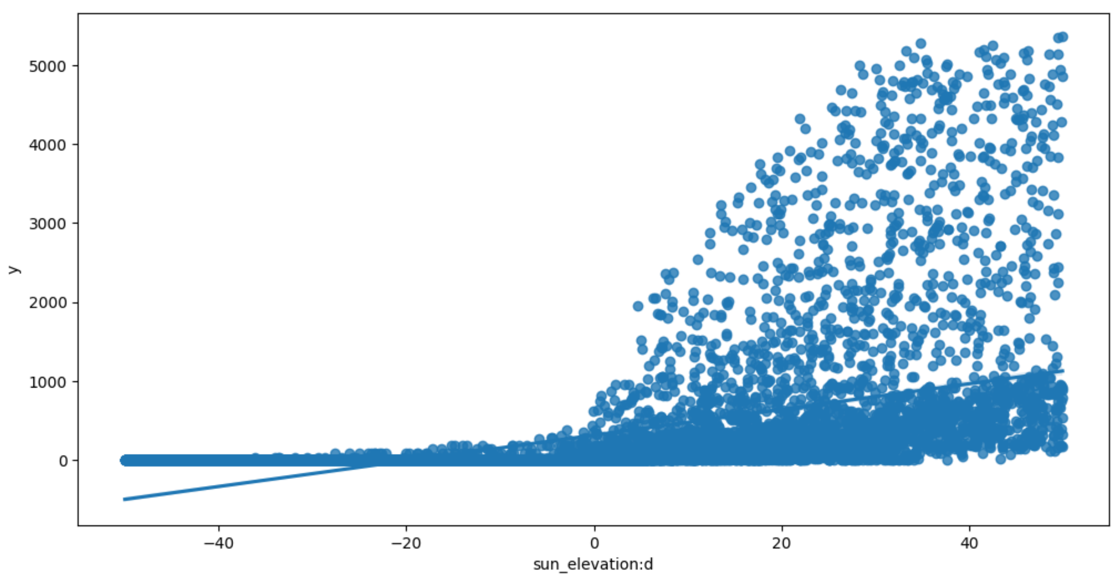
Feature interaction between `direct_rad:W/y` in `train_data` (sample size: 10000)



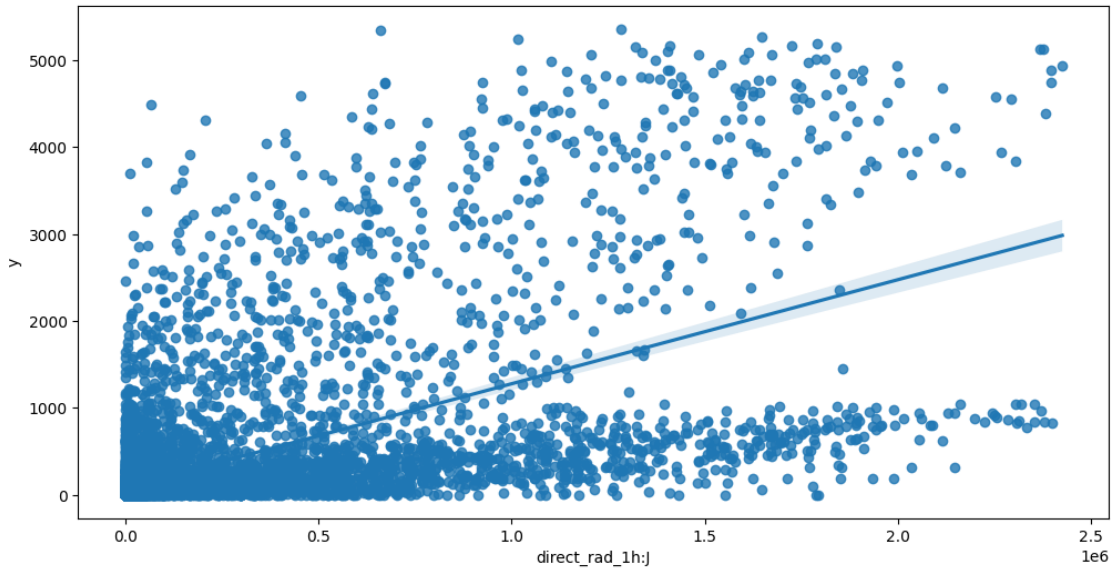
Feature interaction between `diffuse_rad_1h:J/y` in `train_data` (sample size: 10000)



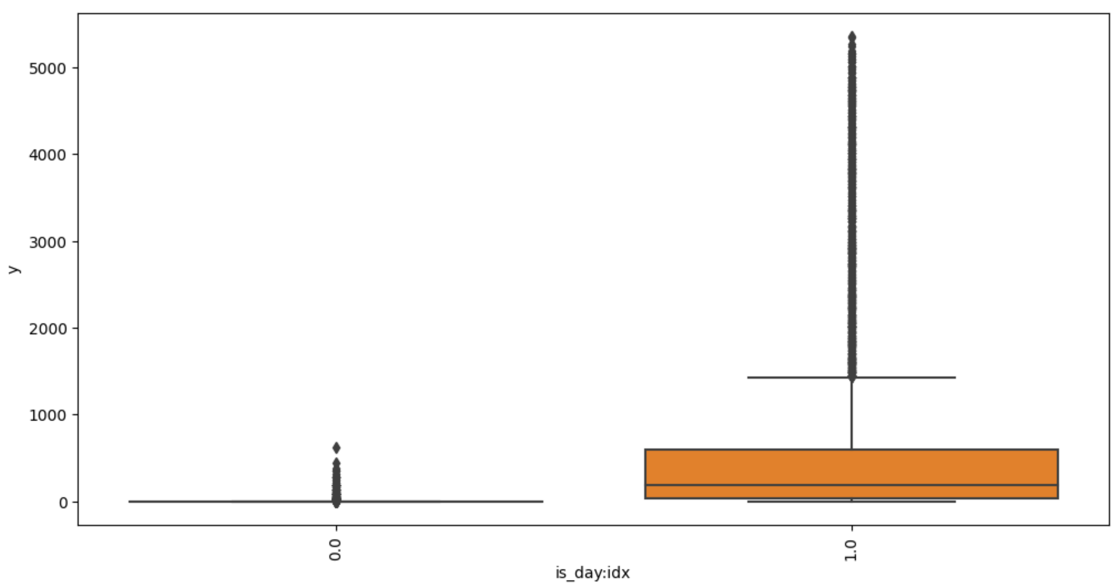
Feature interaction between `sun_elevation:d`/`y` in `train_data` (sample size: 10000)



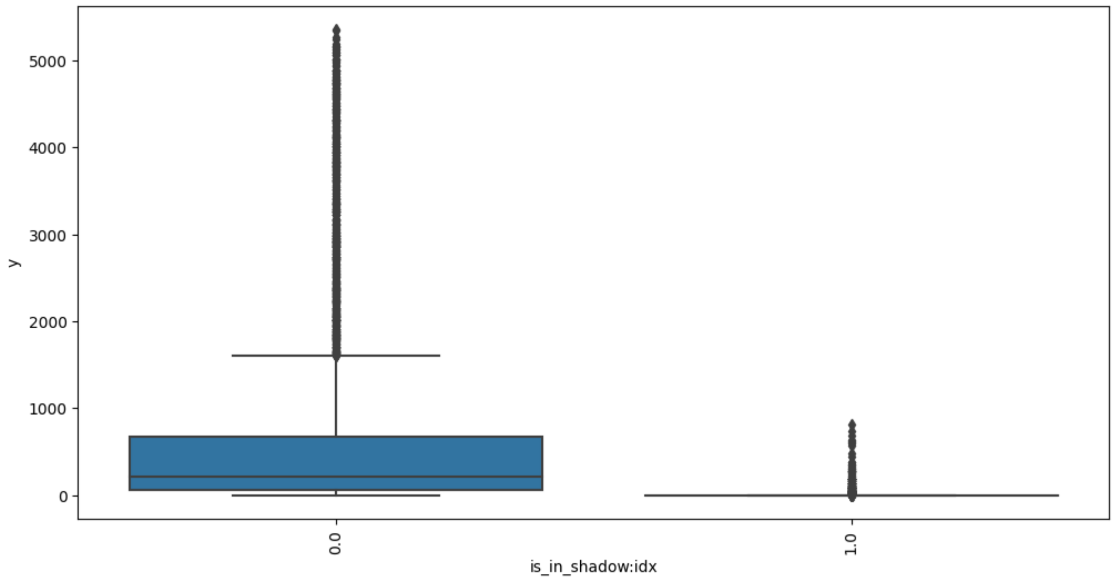
Feature interaction between `direct_rad_1h:J`/`y` in `train_data` (sample size: 10000)



Feature interaction between `is_day:idx/y` in `train_data` (sample size: 10000)



Feature interaction between `is_in_shadow:idx/y` in `train_data` (sample size: 10000)

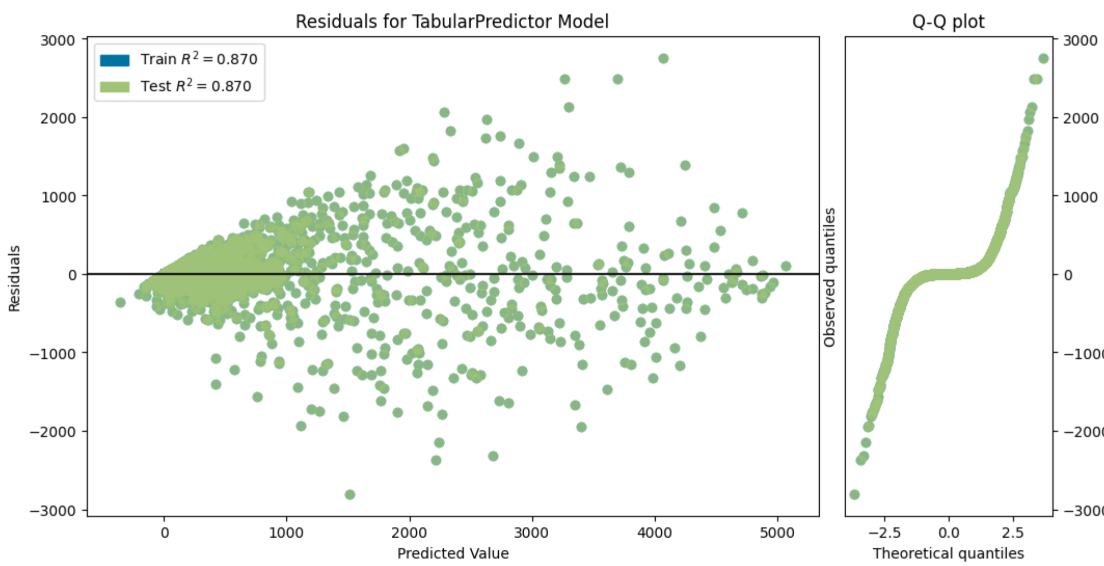


[34]:
```
auto.quick_fit(X_train, "y", show_feature_importance_barplots=True, val_size=0.
↪3, sample=20000)
```

```
No path specified. Models will be saved in:
"AutogluonModels/ag-20231007_083734/"
```

1.1.3 Model Prediction for y

Using validation data for `Test` points



1.1.4 Model Leaderboard

```
       model  score_test   score_val  pred_time_test  pred_time_val  \
0  LightGBMXT -249.164477 -285.431722        0.143977       0.033739

   fit_time  pred_time_test_marginal  pred_time_val_marginal  \
0  32.57896                 0.143977                0.033739

   fit_time_marginal  stack_level  can_infer  fit_order
0           32.57896            1       True          1
```

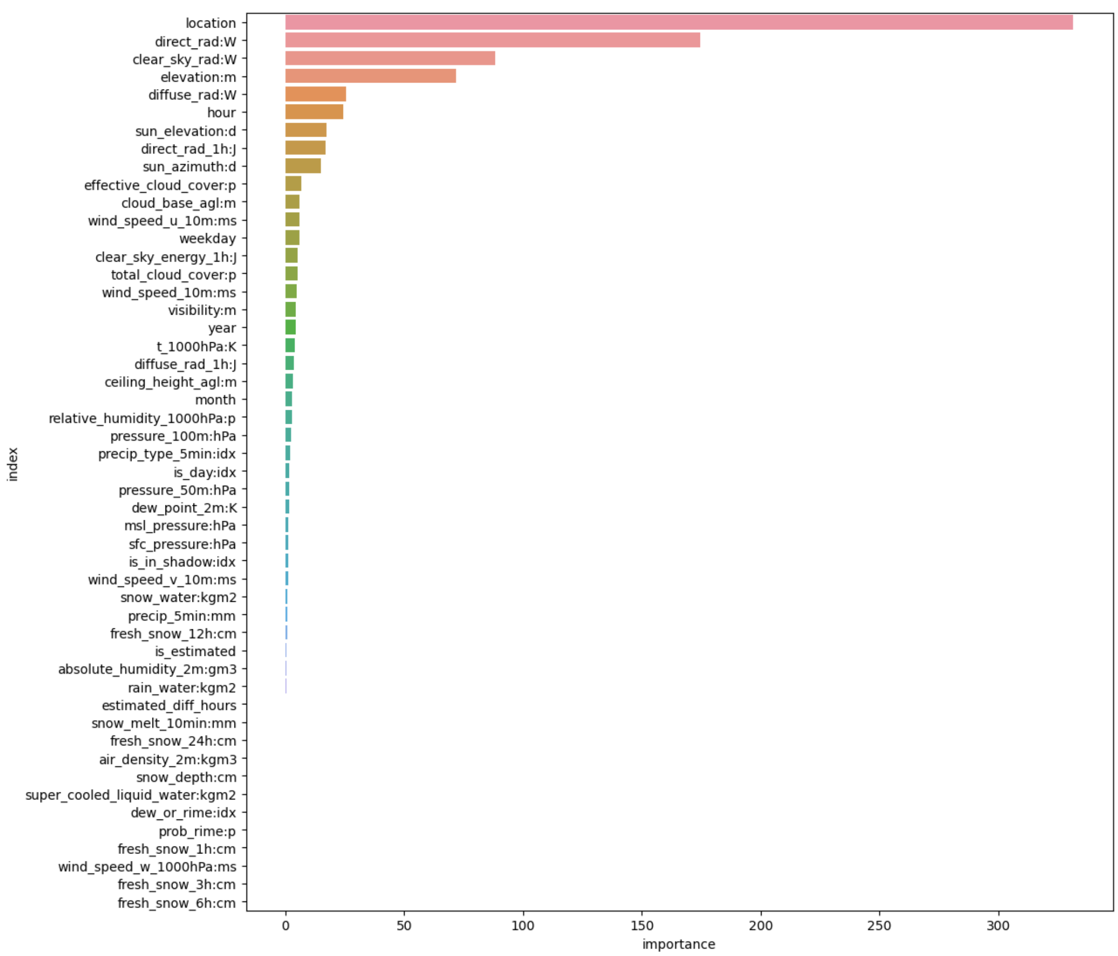
1.1.5 Feature Importance for Trained Model

```
                              importance    stddev       p_value  n  \
location                      331.696169  5.162675  7.040093e-09  5
direct_rad:W                  174.475515  5.570827  1.245466e-07  5
clear_sky_rad:W                88.339881  4.673420  9.364283e-07  5
elevation:m                    71.933615  0.736963  1.321831e-09  5
diffuse_rad:W                  25.495976  3.292982  3.266283e-05  5
hour                           24.161588  1.923359  4.778159e-06  5
sun_elevation:d                17.143152  2.022905  2.284024e-05  5
direct_rad_1h:J                16.726966  1.255815  3.784057e-06  5
sun_azimuth:d                  14.771818  2.007006  3.990487e-05  5
effective_cloud_cover:p         6.673519  1.648372  4.125293e-04  5
cloud_base_agl:m                5.938038  1.699040  7.235088e-04  5
wind_speed_u_10m:ms             5.911503  1.817884  9.501390e-04  5
weekday                         5.732701  2.268904  2.417356e-03  5
clear_sky_energy_1h:J           5.046111  1.187912  3.428176e-04  5
total_cloud_cover:p             4.940198  1.242553  4.422732e-04  5
wind_speed_10m:ms               4.637546  1.572704  1.370225e-03  5
visibility:m                    4.489987  0.913578  1.947971e-04  5
year                            4.271376  2.112551  5.324625e-03  5
t_1000hPa:K                     3.907887  0.955921  3.973957e-04  5
diffuse_rad_1h:J                3.600884  1.023364  7.051564e-04  5
ceiling_height_agl:m            3.064892  1.417966  4.220837e-03  5
month                           2.797475  0.983648  1.567005e-03  5
relative_humidity_1000hPa:p     2.628597  1.800418  1.547250e-02  5
pressure_100m:hPa               2.397624  0.809312  1.346683e-03  5
precip_type_5min:idx            1.804101  1.557007  3.031232e-02  5
is_day:idx                      1.737333  0.336538  1.608290e-04  5
pressure_50m:hPa                1.690660  0.736555  3.413125e-03  5
dew_point_2m:K                  1.652829  0.697696  3.049351e-03  5
msl_pressure:hPa                1.344610  0.583749  3.370896e-03  5
sfc_pressure:hPa                1.284009  0.740240  8.930881e-03  5
is_in_shadow:idx                1.246250  0.470616  2.037303e-03  5
wind_speed_v_10m:ms             1.111493  0.799260  1.794302e-02  5
snow_water:kgm2                 0.771670  0.114084  5.569327e-05  5
precip_5min:mm                  0.726523  0.991911  8.840236e-02  5
```

fresh_snow_12h:cm	0.619026	0.392833	1.218547e-02	5
is_estimated	0.586491	0.786757	8.543233e-02	5
absolute_humidity_2m:gm3	0.511014	0.542340	5.142410e-02	5
rain_water:kgm2	0.485744	0.550613	5.990403e-02	5
estimated_diff_hours	0.176034	0.237801	8.660593e-02	5
snow_melt_10min:mm	0.106574	0.025576	3.692098e-04	5
fresh_snow_24h:cm	0.097888	0.220230	1.882677e-01	5
air_density_2m:kgm3	0.093666	0.400342	3.142530e-01	5
snow_depth:cm	0.047270	0.043140	3.521699e-02	5
super_cooled_liquid_water:kgm2	0.010261	0.236587	4.637040e-01	5
dew_or_rime:idx	0.006189	0.009752	1.144442e-01	5
prob_rime:p	0.000000	0.000000	5.000000e-01	5
fresh_snow_1h:cm	0.000000	0.000000	5.000000e-01	5
wind_speed_w_1000hPa:ms	-0.000081	0.000548	6.211064e-01	5
fresh_snow_3h:cm	-0.001715	0.004855	7.631630e-01	5
fresh_snow_6h:cm	-0.005063	0.007336	9.011816e-01	5

	p99_high	p99_low
location	342.326189	321.066149
direct_rad:W	185.945924	163.005105
clear_sky_rad:W	97.962518	78.717244
elevation:m	73.451032	70.416198
diffuse_rad:W	32.276272	18.715681
hour	28.121812	20.201365
sun_elevation:d	21.308342	12.977962
direct_rad_1h:J	19.312706	14.141227
sun_azimuth:d	18.904272	10.639365
effective_cloud_cover:p	10.067539	3.279499
cloud_base_agl:m	9.436385	2.439691
wind_speed_u_10m:ms	9.654552	2.168454
weekday	10.404406	1.060996
clear_sky_energy_1h:J	7.492039	2.600184
total_cloud_cover:p	7.498631	2.381765
wind_speed_10m:ms	7.875766	1.399326
visibility:m	6.371057	2.608918
year	8.621147	-0.078395
t_1000hPa:K	5.876141	1.939633
diffuse_rad_1h:J	5.708005	1.493763
ceiling_height_agl:m	5.984505	0.145280
month	4.822820	0.772131
relative_humidity_1000hPa:p	6.335681	-1.078488
pressure_100m:hPa	4.064010	0.731238
precip_type_5min:idx	5.010001	-1.401799
is_day:idx	2.430270	1.044396
pressure_50m:hPa	3.207236	0.174084
dew_point_2m:K	3.089395	0.216262
msl_pressure:hPa	2.546556	0.142663
sfc_pressure:hPa	2.808173	-0.240156

is_in_shadow:idx	2.215255	0.277245
wind_speed_v_10m:ms	2.757181	-0.534195
snow_water:kgm2	1.006570	0.536769
precip_5min:mm	2.768882	-1.315835
fresh_snow_12h:cm	1.427874	-0.189823
is_estimated	2.206434	-1.033452
absolute_humidity_2m:gm3	1.627700	-0.605672
rain_water:kgm2	1.619463	-0.647976
estimated_diff_hours	0.665670	-0.313601
snow_melt_10min:mm	0.159236	0.053913
fresh_snow_24h:cm	0.551345	-0.355570
air_density_2m:kgm3	0.917976	-0.730645
snow_depth:cm	0.136095	-0.041555
super_cooled_liquid_water:kgm2	0.497397	-0.476876
dew_or_rime:idx	0.026269	-0.013891
prob_rime:p	0.000000	0.000000
fresh_snow_1h:cm	0.000000	0.000000
wind_speed_w_1000hPa:ms	0.001047	-0.001209
fresh_snow_3h:cm	0.008281	-0.011711
fresh_snow_6h:cm	0.010042	-0.020168



1.1.6 Rows with the highest prediction error

Rows in this category worth inspecting for the causes of the error

ds	absolute_humidity_2m:gm3	air_density_2m:kgm3	\
2021-08-31 12:00:00	10.6	1.240	
2022-04-19 08:00:00	5.4	1.243	
2022-04-19 08:00:00	5.4	1.238	
2022-04-19 08:00:00	5.4	1.238	
2022-04-19 08:00:00	5.4	1.243	
2019-08-24 10:00:00	10.4	1.214	
2022-06-25 13:00:00	10.7	1.165	
2020-07-27 12:00:00	12.1	1.204	
2020-04-19 09:00:00	5.6	1.268	
2022-08-12 12:00:00	10.4	1.228	

ds	ceiling_height_agl:m	clear_sky_energy_1h:J	\
2021-08-31 12:00:00	932.400024	2157642.500	
2022-04-19 08:00:00	NaN	1415330.750	
2022-04-19 08:00:00	NaN	1416421.750	
2022-04-19 08:00:00	NaN	1416421.750	
2022-04-19 08:00:00	NaN	1415330.750	
2019-08-24 10:00:00	1145.500000	2091485.250	
2022-06-25 13:00:00	8184.100098	2917584.750	
2020-07-27 12:00:00	5779.100098	2775520.500	
2020-04-19 09:00:00	841.200012	1839072.625	
2022-08-12 12:00:00	1176.900024	2546188.500	

ds	clear_sky_rad:W	cloud_base_agl:m	dew_or_rime:idx	\
2021-08-31 12:00:00	593.000000	210.199997	0.0	
2022-04-19 08:00:00	452.500000	NaN	0.0	
2022-04-19 08:00:00	452.899994	NaN	0.0	
2022-04-19 08:00:00	452.899994	NaN	0.0	
2022-04-19 08:00:00	452.500000	NaN	0.0	
2019-08-24 10:00:00	612.299988	1145.500000	0.0	
2022-06-25 13:00:00	787.099976	2588.000000	0.0	
2020-07-27 12:00:00	765.799988	2804.600098	0.0	
2020-04-19 09:00:00	557.700012	697.400024	0.0	
2022-08-12 12:00:00	702.200012	602.700012	0.0	

	dew_point_2m:K	diffuse_rad:W	diffuse_rad_1h:J	…	\
ds				…	

```
2021-08-31 12:00:00      285.100006     160.399994      538968.31250  …
2022-04-19 08:00:00      275.200012      79.800003      273179.90625  …
2022-04-19 08:00:00      275.200012      80.599998      275853.40625  …
2022-04-19 08:00:00      275.200012      80.599998      275853.40625  …
2022-04-19 08:00:00      275.200012      79.800003      273179.90625  …
2019-08-24 10:00:00      285.100006     217.100006      801617.87500  …
2022-06-25 13:00:00      286.000000     176.699997      539379.37500  …
2020-07-27 12:00:00      287.299988     177.600006      562589.12500  …
2020-04-19 09:00:00      275.600006     122.699997      426257.50000  …
2022-08-12 12:00:00      285.000000     191.699997      700617.00000  …

                     estimated_diff_hours  is_estimated  location  hour  \
ds
2021-08-31 12:00:00                   0.0         False         A    12
2022-04-19 08:00:00                   0.0         False         A     8
2022-04-19 08:00:00                   0.0         False         C     8
2022-04-19 08:00:00                   0.0         False         C     8
2022-04-19 08:00:00                   0.0         False         A     8
2019-08-24 10:00:00                   0.0         False         A    10
2022-06-25 13:00:00                   0.0         False         A    13
2020-07-27 12:00:00                   0.0         False         A    12
2020-04-19 09:00:00                   0.0         False         A     9
2022-08-12 12:00:00                   0.0         False         A    12

                     weekday  month  year        y       y_pred        error
ds
2021-08-31 12:00:00        1      8  2021  4317.50  1513.236938  2804.263062
2022-04-19 08:00:00        1      4  2022  1311.86  4069.547363  2757.687363
2022-04-19 08:00:00        1      4  2022   490.00   500.201965  2757.687363
2022-04-19 08:00:00        1      4  2022   490.00  4069.547363  2757.687363
2022-04-19 08:00:00        1      4  2022  1311.86   500.201965  2757.687363
2019-08-24 10:00:00        5      8  2019   768.90  3259.254150  2490.354150
2022-06-25 13:00:00        5      6  2022  1200.32  3690.502930  2490.182930
2020-07-27 12:00:00        0      7  2020  4585.46  2212.621582  2372.838418
2020-04-19 09:00:00        6      4  2020  4993.12  2677.911621  2315.208379
2022-08-12 12:00:00        4      8  2022  4391.64  2239.918457  2151.721543

[10 rows x 53 columns]
```

2 Starting

[35]:
```python
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
```

```
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 82
Now creating submission number: 83
New filename: submission_83_jorge
```

[36]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
train_data = TabularDataset('X_train_raw.csv')
train_data.drop(columns=['ds'], inplace=True)

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*10
presets = 'best_quality'
```

```
Loaded data from: X_train_raw.csv | Columns = 52 / 52 | Rows = 93024 -> 93024
```

[ ]:
```
predictor = TabularPredictor(label=label, eval_metric=metric,␣
↪path=f"AutogluonModels/{new_filename}").fit(train_data, presets=presets,␣
↪time_limit=time_limit)
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_82_jorge"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 180s
AutoGluon will save models to "AutogluonModels/submission_82_jorge/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   19.58 GB / 494.38 GB (4.0%)
Train Data Rows:    136724
Train Data Columns: 50
Label Column: y
Preprocessing data …
```

```
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, -0.0, 247.8577,
717.45424)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    6093.6 MB
        Train Data (Original)  Memory Usage: 64.81 MB (1.1% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
                Fitting CategoryFeatureGenerator…
                        Fitting CategoryMemoryMinimizeFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Types of features in original data (raw dtype, special dtypes):
                ('float', [])  : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])    :  4 | ['hour', 'weekday', 'month', 'year']
                ('object', []) :  2 | ['is_estimated', 'location']
        Types of features in processed data (raw dtype, special dtypes):
                ('category', []) :  2 | ['is_estimated', 'location']
                ('float', [])    : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])      :  4 | ['hour', 'weekday', 'month', 'year']
        0.4s = Fit runtime
        50 features in original data used to generate 50 features in processed
data.
        Train Data (Processed) Memory Usage: 52.78 MB (0.9% of available memory)
Data preprocessing and feature engineering runtime = 0.46s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
```

```
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 119.66s of the
179.54s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 2711.1s compared to 155.45s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 109.59s of the
169.46s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 2019.42s compared to 142.35s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 102.04s of the
161.91s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -51.2173         = Validation score   (-mean_absolute_error)
        57.03s   = Training   runtime
        244.85s  = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 8.22s of the 68.09s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -63.6844         = Validation score   (-mean_absolute_error)
        7.47s    = Training   runtime
        3.97s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 179.54s of the
```

```
57.53s of remaining time.
        -51.2137         = Validation score   (-mean_absolute_error)
        0.41s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 57.11s of the
57.1s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -49.5271         = Validation score   (-mean_absolute_error)
        48.05s   = Training   runtime
        202.48s  = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 179.54s of the
-19.21s of remaining time.
        -49.5271         = Validation score   (-mean_absolute_error)
        0.0s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 199.28s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_82_jorge/")
```

[ ]:
```
predictors = [predictor, predictor, predictor]
```

3 Submit

[38]:
```
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 52 / 52 | Rows = 93024 -> 93024
Loaded data from: X_test_raw.csv | Columns = 51 / 51 | Rows = 2160 -> 2160
```

[39]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
↪"location"], left_on=["ds", "location"])

#test_data_merged
```

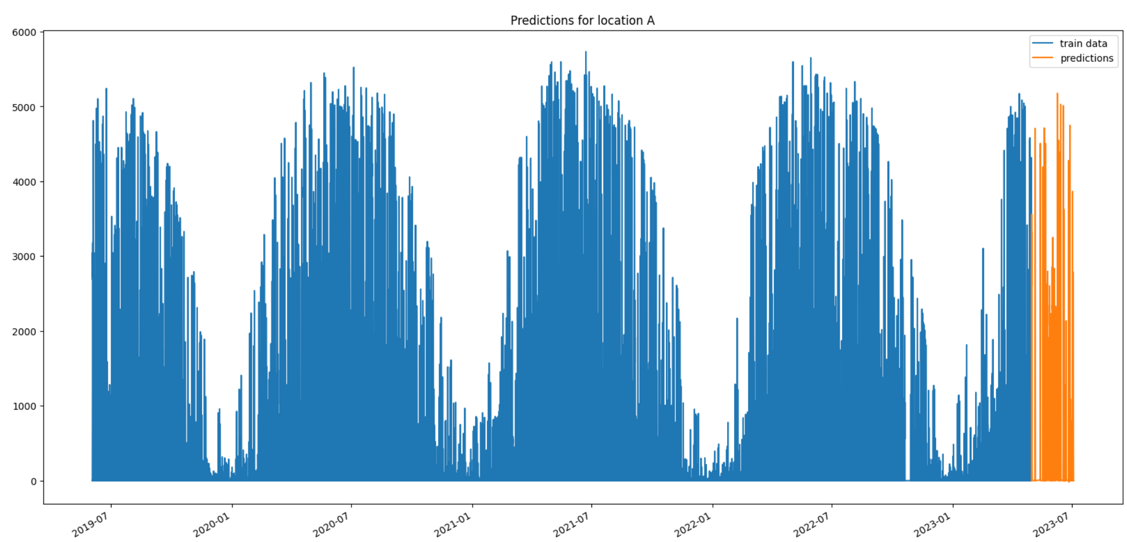
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160

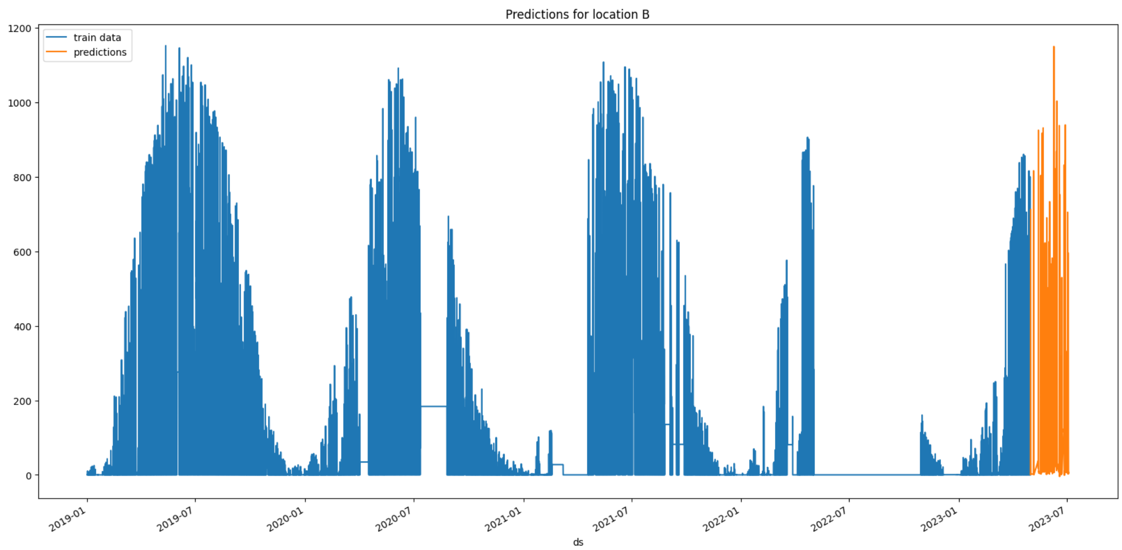
[40]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
  ↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)
```

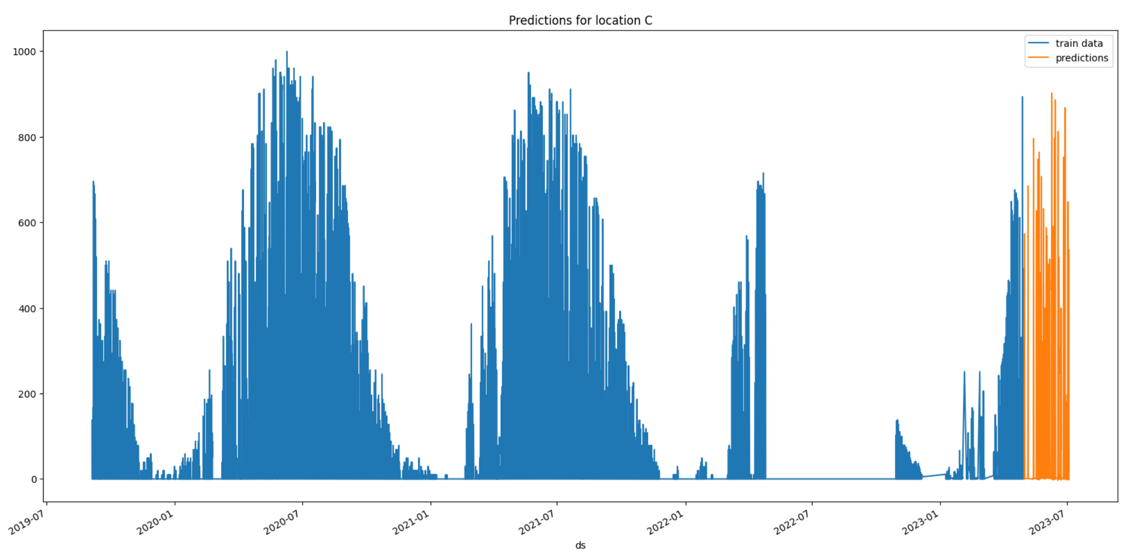
[41]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
  ↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```







[42]:
```
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[42]:

	id	prediction
0	0	0.211684
1	1	0.516265
2	2	1.031603

```
3        3   52.105175
4        4  288.467529
..     …         …
715   2155   72.857269
716   2156   36.051491
717   2157   13.137769
718   2158   -1.017557
719   2159   -0.760469

[2160 rows x 2 columns]
```

[43]:
```python
# Save the submission DataFrame to submissions folder, create new name based on
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
↪index=False)
```

```
Saving submission to submissions/submission_83_jorge.csv
```

[44]:
```python
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_all.ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_all.ipynb to pdf
[NbConvertApp] Support files will be in notebook_pdfs/submission_83_jorge_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_83_jorge_files/notebook_pdfs
[NbConvertApp] Writing 141076 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 1716055 bytes to notebook_pdfs/submission_83_jorge.pdf
```

[44]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_83_jorge.pdf', 'autogluon_all.ipynb'], returncode=0)
```

[45]:
```python
predictor.fit_summary(show_plot=True)
```

```
*** Summary of fit() ***
Estimated performance of each model:
                  model  score_val  pred_time_val    fit_time
pred_time_val_marginal  fit_time_marginal  stack_level  can_infer  fit_order
```

```
0    LightGBMXT_BAG_L2 -49.527149     451.300462  112.549396
202.476526          48.048242            2       True          4
1  WeightedEnsemble_L3 -49.527149     451.301551  112.551775
0.001090           0.002379            3       True          5
2  WeightedEnsemble_L2 -51.213662     248.825019   64.910360
0.001083           0.409206            2       True          3
3    LightGBMXT_BAG_L1 -51.217300     244.854969   57.026824
244.854969          57.026824            1       True          1
4      LightGBM_BAG_L1 -63.684434       3.968967    7.474330
3.968967           7.474330            1       True          2
Number of models trained: 5
Types of models trained:
{'WeightedEnsembleModel', 'StackerEnsembleModel_LGB'}
Bagging used: True  (with 8 folds)
Multi-layer stack-ensembling used: True  (with 3 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('category', []) :  2 | ['is_estimated', 'location']
('float', [])    : 44 | ['absolute_humidity_2m:gm3', 'air_density_2m:kgm3',
'ceiling_height_agl:m', 'clear_sky_energy_1h:J', 'clear_sky_rad:W', …]
('int', [])      :  4 | ['hour', 'weekday', 'month', 'year']
*** End of fit() summary ***
```

[45]:
```
{'model_types': {'LightGBMXT_BAG_L1': 'StackerEnsembleModel_LGB',
  'LightGBM_BAG_L1': 'StackerEnsembleModel_LGB',
  'WeightedEnsemble_L2': 'WeightedEnsembleModel',
  'LightGBMXT_BAG_L2': 'StackerEnsembleModel_LGB',
  'WeightedEnsemble_L3': 'WeightedEnsembleModel'},
 'model_performance': {'LightGBMXT_BAG_L1': -51.21730013851277,
  'LightGBM_BAG_L1': -63.684434475206324,
  'WeightedEnsemble_L2': -51.2136616576165,
  'LightGBMXT_BAG_L2': -49.527148759180335,
  'WeightedEnsemble_L3': -49.527148759180335},
 'model_best': 'WeightedEnsemble_L3',
 'model_paths': {'LightGBMXT_BAG_L1':
'AutogluonModels/submission_82_jorge/models/LightGBMXT_BAG_L1/',
  'LightGBM_BAG_L1':
'AutogluonModels/submission_82_jorge/models/LightGBM_BAG_L1/',
  'WeightedEnsemble_L2':
'AutogluonModels/submission_82_jorge/models/WeightedEnsemble_L2/',
  'LightGBMXT_BAG_L2':
'AutogluonModels/submission_82_jorge/models/LightGBMXT_BAG_L2/',
  'WeightedEnsemble_L3':
'AutogluonModels/submission_82_jorge/models/WeightedEnsemble_L3/'},
 'model_fit_times': {'LightGBMXT_BAG_L1': 57.02682399749756,
  'LightGBM_BAG_L1': 7.474329948425293,
  'WeightedEnsemble_L2': 0.4092061519622803,
```

```
 'LightGBMXT_BAG_L2': 48.04824185371399,
 'WeightedEnsemble_L3': 0.0023789405822753906},
'model_pred_times': {'LightGBMXT_BAG_L1': 244.85496854782104,
 'LightGBM_BAG_L1': 3.9689671993255615,
 'WeightedEnsemble_L2': 0.0010828971862792969,
 'LightGBMXT_BAG_L2': 202.47652578353882,
 'WeightedEnsemble_L3': 0.0010898113250732422},
'num_bag_folds': 8,
'max_stack_level': 3,
'model_hyperparams': {'LightGBMXT_BAG_L1': {'use_orig_features': True,
  'max_base_models': 25,
  'max_base_models_per_type': 5,
  'save_bag_folds': True},
 'LightGBM_BAG_L1': {'use_orig_features': True,
  'max_base_models': 25,
  'max_base_models_per_type': 5,
  'save_bag_folds': True},
 'WeightedEnsemble_L2': {'use_orig_features': False,
  'max_base_models': 25,
  'max_base_models_per_type': 5,
  'save_bag_folds': True},
 'LightGBMXT_BAG_L2': {'use_orig_features': True,
  'max_base_models': 25,
  'max_base_models_per_type': 5,
  'save_bag_folds': True},
 'WeightedEnsemble_L3': {'use_orig_features': False,
  'max_base_models': 25,
  'max_base_models_per_type': 5,
  'save_bag_folds': True}},
'leaderboard':                  model  score_val  pred_time_val    fit_time  \
0    LightGBMXT_BAG_L2 -49.527149     451.300462  112.549396
1  WeightedEnsemble_L3 -49.527149     451.301551  112.551775
2  WeightedEnsemble_L2 -51.213662     248.825019   64.910360
3    LightGBMXT_BAG_L1 -51.217300     244.854969   57.026824
4      LightGBM_BAG_L1 -63.684434       3.968967    7.474330

   pred_time_val_marginal  fit_time_marginal  stack_level  can_infer  \
0              202.476526          48.048242            2       True
1                0.001090           0.002379            3       True
2                0.001083           0.409206            2       True
3              244.854969          57.026824            1       True
4                3.968967           7.474330            1       True

   fit_order
0          4
1          5
2          3
```

```
3          1
4          2  }
```

[49]:

[49]:

```
                        ds  absolute_humidity_2m:gm3  air_density_2m:kgm3  \
0      2019-06-02 22:00:00                       7.7                1.230
1      2019-06-02 23:00:00                       7.7                1.225
2      2019-06-03 00:00:00                       7.7                1.221
3      2019-06-03 01:00:00                       8.2                1.218
4      2019-06-03 02:00:00                       8.8                1.219
…                      …                       …                  …
93019 2023-04-30 19:00:00                       4.4                1.274
93020 2023-04-30 20:00:00                       4.4                1.278
93021 2023-04-30 21:00:00                       4.4                1.279
93022 2023-04-30 22:00:00                       4.4                1.279
93023 2023-04-30 23:00:00                       4.4                1.280

       ceiling_height_agl:m  clear_sky_energy_1h:J  clear_sky_rad:W  \
0                    1744.9                    0.0              0.0
1                    1703.6                    0.0              0.0
2                    1668.1                    0.0              0.0
3                    1388.4                    0.0              0.0
4                    1108.5                 6546.9              9.8
…                       …                     …               …
93019                1474.2               156770.7             13.4
93020                1427.3                 7917.1              0.0
93021                1558.1                    0.0              0.0
93022                1446.6                    0.0              0.0
93023                 897.2                    0.0              0.0

       cloud_base_agl:m  dew_or_rime:idx  dew_point_2m:K  diffuse_rad:W  …  \
0                1744.9              0.0           280.3            0.0  …
1                1703.6              0.0           280.3            0.0  …
2                1668.1              0.0           280.2            0.0  …
3                1388.4              0.0           281.3            0.0  …
4                1108.5              0.0           282.3            4.3  …
…                   …               …              …            …   …
93019             557.0              0.0           272.1            8.8  …
93020             541.7              0.0           272.0            0.0  …
93021             601.5              0.0           271.9            0.0  …
93022             540.7              0.0           271.9            0.0  …
93023             569.5              0.0           272.0            0.0  …

       wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  estimated_diff_hours  \
0                     -0.8                     -0.0                   0.0
1                      0.0                     -0.0                   0.0
```

```
2                   0.7                    -0.0                  0.0
3                   0.8                    -0.0                  0.0
4                   1.0                    -0.0                  0.0
…                 …                      …                   …
93019               1.8                    -0.0                 35.0
93020               1.9                    -0.0                 36.0
93021               2.4                    -0.0                 37.0
93022               2.4                    -0.0                 38.0
93023               2.1                    -0.0                 39.0

       is_estimated      y  location  hour  weekday  month  year
0             False   0.00         A    22        6      6  2019
1             False   0.00         A    23        6      6  2019
2             False   0.00         A     0        0      6  2019
3             False   0.00         A     1        0      6  2019
4             False  19.36         A     2        0      6  2019
…             …    …       …   …       …    …   …
93019          True  50.96         C    19        6      4  2023
93020          True   2.94         C    20        6      4  2023
93021          True   0.00         C    21        6      4  2023
93022          True  -0.00         C    22        6      4  2023
93023          True  -0.00         C    23        6      4  2023

[93024 rows x 52 columns]
```

[53]:

```python
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictor.feature_importance(feature_stage="original", data=estimated)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds']
Computing feature importance via permutation shuffling for 50 features using
4418 rows with 5 shuffle sets…
        2640.42s        = Expected runtime (528.08s per shuffle set)
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
/Users/jorgensandhaug/Desktop/tdt4173/data/autogluon_all.ipynb Cell 22 line 6
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
 ↪autogluon_all.ipynb#X26sZmlsZQ%3D%3D?line=3'>4</a> estimated =␣
 ↪train_data_with_dates[train_data_with_dates["ds"] >= split_time]
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
 ↪autogluon_all.ipynb#X26sZmlsZQ%3D%3D?line=4'>5</a> estimated =␣
 ↪estimated[estimated["location"] == location]
```

```
----> <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
 ↪autogluon_all.ipynb#X26sZmlsZQ%3D%3D?line=5'>6</a> predictor.
 ↪feature_importance(feature_stage="original", data=estimated)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
 ↪tabular/predictor/predictor.py:2425, in TabularPredictor.
 ↪feature_importance(self, data, model, features, feature_stage, subsample_size,␣
 ↪time_limit, num_shuffle_sets, include_confidence_band, confidence_level,␣
 ↪silent)
   2422 if num_shuffle_sets is None:
   2423     num_shuffle_sets = 10 if time_limit else 5
-> 2425 fi_df = self._learner.get_feature_importance(
   2426     model=model,
   2427     X=data,
   2428     features=features,
   2429     feature_stage=feature_stage,
   2430     subsample_size=subsample_size,
   2431     time_limit=time_limit,
   2432     num_shuffle_sets=num_shuffle_sets,
   2433     silent=silent,
   2434 )
   2436 if include_confidence_band:
   2437     if confidence_level <= 0.5 or confidence_level >= 1.0:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
 ↪tabular/learner/abstract_learner.py:870, in AbstractTabularLearner.
 ↪get_feature_importance(self, model, X, y, features, feature_stage,␣
 ↪subsample_size, silent, **kwargs)
    867         X = X.drop(columns=unused_features)
    869     if feature_stage == "original":
--> 870         return trainer._get_feature_importance_raw(
    871             model=model, X=X, y=y, features=features,␣
 ↪subsample_size=subsample_size, transform_func=self.transform_features,␣
 ↪silent=silent, **kwargs
    872         )
    873     X = self.transform_features(X)
    874 else:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2574, in AbstractTrainer.
 ↪_get_feature_importance_raw(self, X, y, model, eval_metric, **kwargs)
   2572 model: AbstractModel = self.load_model(model)
   2573 predict_func_kwargs = dict(model=model)
-> 2574 return compute_permutation_feature_importance(
   2575     X=X,
   2576     y=y,
   2577     predict_func=predict_func,
   2578     predict_func_kwargs=predict_func_kwargs,
   2579     eval_metric=eval_metric,
   2580     quantile_levels=self.quantile_levels,
```

```
   2581     **kwargs,
   2582 )

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪utils/utils.py:867, in compute_permutation_feature_importance(X, y,␣
 ↪predict_func, eval_metric, features, subsample_size, num_shuffle_sets,␣
 ↪predict_func_kwargs, transform_func, transform_func_kwargs, time_limit,␣
 ↪silent, log_prefix, importance_as_list, random_state, **kwargs)
    865 else:
    866     X_raw_transformed = X_raw if transform_func is None else␣
 ↪transform_func(X_raw, **transform_func_kwargs)
--> 867 y_pred = predict_func(X_raw_transformed, **predict_func_kwargs)
    869 row_index = 0
    870 for feature in parallel_computed_features:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:749, in AbstractTrainer.predict(self, X, model)
    747     model = self._get_best()
    748 cascade = isinstance(model, list)
--> 749 return self._predict_model(X, model, cascade=cascade)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2388, in AbstractTrainer._predict_model(self, X,␣
 ↪model, model_pred_proba_dict, cascade)
   2387 def _predict_model(self, X, model, model_pred_proba_dict=None,␣
 ↪cascade=False):
-> 2388     y_pred_proba = self._predict_proba_model(X=X, model=model,␣
 ↪model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)
   2389     return get_pred_from_proba(y_pred_proba=y_pred_proba,␣
 ↪problem_type=self.problem_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2392, in AbstractTrainer.
 ↪_predict_proba_model(self, X, model, model_pred_proba_dict, cascade)
   2391 def _predict_proba_model(self, X, model, model_pred_proba_dict=None,␣
 ↪cascade=False):
-> 2392     return self.get_pred_proba_from_model(model=model, X=X,␣
 ↪model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:769, in AbstractTrainer.
 ↪get_pred_proba_from_model(self, model, X, model_pred_proba_dict, cascade)
    767 else:
    768     models = [model]
--> 769 model_pred_proba_dict = self.get_model_pred_proba_dict(X=X,␣
 ↪models=models, model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)
    770 if not isinstance(model, str):
    771     model = model.name
```

```
File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪trainer/abstract_trainer.py:1018, in AbstractTrainer.
↪get_model_pred_proba_dict(self, X, models, model_pred_proba_dict,␣
↪model_pred_time_dict, record_pred_time, use_val_cache, cascade,␣
↪cascade_threshold)
   1016     else:
   1017         preprocess_kwargs = dict(infer=False,␣
 ↪model_pred_proba_dict=model_pred_proba_dict)
-> 1018     model_pred_proba_dict[model_name] = model.predict_proba(X,␣
 ↪**preprocess_kwargs)
   1019 else:
   1020     model_pred_proba_dict[model_name] = model.predict_proba(X)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪models/ensemble/bagged_ensemble_model.py:346, in BaggedEnsembleModel.
↪predict_proba(self, X, normalize, **kwargs)
    344 model = self.load_child(self.models[0])
    345 X = self.preprocess(X, model=model, **kwargs)
--> 346 pred_proba = model.predict_proba(X=X, preprocess_nonadaptive=False,␣
 ↪normalize=normalize)
    347 for model in self.models[1:]:
    348     model = self.load_child(model)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪models/abstract/abstract_model.py:931, in AbstractModel.predict_proba(self, X,␣
↪normalize, **kwargs)
    929 if normalize is None:
    930     normalize = self.normalize_pred_probas
--> 931 y_pred_proba = self._predict_proba(X=X, **kwargs)
    932 if normalize:
    933     y_pred_proba = normalize_pred_probas(y_pred_proba, self.problem_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/models/lgb/lgb_model.py:234, in LGBModel._predict_proba(self, X,␣
↪num_cpus, **kwargs)
    231 def _predict_proba(self, X, num_cpus=0, **kwargs):
    232     X = self.preprocess(X, **kwargs)
--> 234     y_pred_proba = self.model.predict(X, num_threads=num_cpus)
    235     if self.problem_type == REGRESSION:
    236         return y_pred_proba

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
↪py:3538, in Booster.predict(self, data, start_iteration, num_iteration,␣
↪raw_score, pred_leaf, pred_contrib, data_has_header, is_reshape, **kwargs)
   3536     else:
   3537         num_iteration = -1
-> 3538 return predictor.predict(data, start_iteration, num_iteration,
   3539                          raw_score, pred_leaf, pred_contrib,
   3540                          data_has_header, is_reshape)
```

```
File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
↪py:848, in _InnerPredictor.predict(self, data, start_iteration, num_iteration,␣
↪raw_score, pred_leaf, pred_contrib, data_has_header, is_reshape)
    846     preds, nrow = self.__pred_for_csc(data, start_iteration,␣
↪num_iteration, predict_type)
    847 elif isinstance(data, np.ndarray):
--> 848     preds, nrow = self.__pred_for_np2d(data, start_iteration,␣
↪num_iteration, predict_type)
    849 elif isinstance(data, list):
    850     try:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
↪py:938, in _InnerPredictor.__pred_for_np2d(self, mat, start_iteration,␣
↪num_iteration, predict_type)
    936     return preds, nrow
    937 else:
--> 938     return inner_predict(mat, start_iteration, num_iteration,␣
↪predict_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
↪py:908, in _InnerPredictor.__pred_for_np2d.<locals>.inner_predict(mat,␣
↪start_iteration, num_iteration, predict_type, preds)
    906     raise ValueError("Wrong length of pre-allocated predict array")
    907 out_num_preds = ctypes.c_int64(0)
--> 908 _safe_call(_LIB.LGBM_BoosterPredictForMat(
    909     self.handle,
    910     ptr_data,
    911     ctypes.c_int(type_ptr_data),
    912     ctypes.c_int32(mat.shape[0]),
    913     ctypes.c_int32(mat.shape[1]),
    914     ctypes.c_int(C_API_IS_ROW_MAJOR),
    915     ctypes.c_int(predict_type),
    916     ctypes.c_int(start_iteration),
    917     ctypes.c_int(num_iteration),
    918     c_str(self.pred_parameter),
    919     ctypes.byref(out_num_preds),
    920     preds.ctypes.data_as(ctypes.POINTER(ctypes.c_double)))
    921 if n_preds != out_num_preds.value:
    922     raise ValueError("Wrong length for predict results")

KeyboardInterrupt:
```

[ ]:
```
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictor.feature_importance(feature_stage="original", data=observed)
```

```
Computing feature importance via permutation shuffling for 50 features using
5000 rows with 10 shuffle sets… Time limit: 120s…
        6376.36s        = Expected runtime (637.64s per shuffle set)
        505.35s = Actual runtime (Completed 1 of 10 shuffle sets) (Early
stopping due to lack of time…)
```

[ ]:

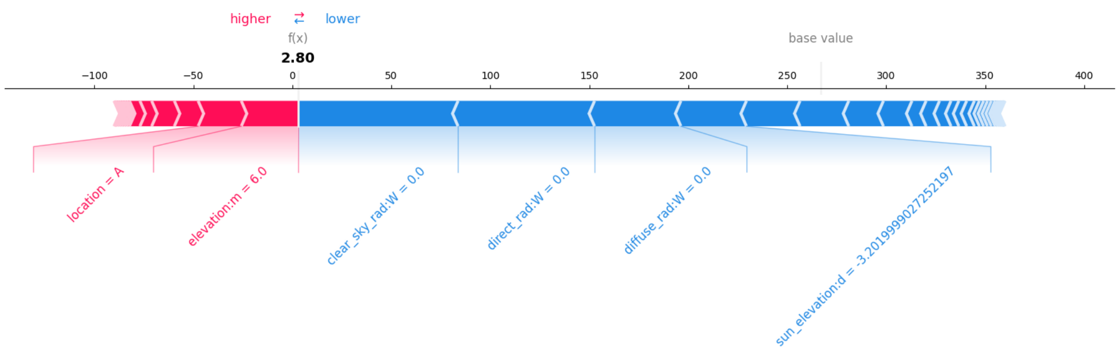
	importance	stddev	p_value	n	p99_high \
direct_rad:W	225.838822	NaN	NaN	1	NaN
clear_sky_rad:W	208.653183	NaN	NaN	1	NaN
diffuse_rad:W	91.020893	NaN	NaN	1	NaN
sun_elevation:d	84.803063	NaN	NaN	1	NaN
clear_sky_energy_1h:J	41.630369	NaN	NaN	1	NaN
hour	39.231764	NaN	NaN	1	NaN
sun_azimuth:d	38.369715	NaN	NaN	1	NaN
cloud_base_agl:m	31.783934	NaN	NaN	1	NaN
weekday	28.542697	NaN	NaN	1	NaN
direct_rad_1h:J	28.482953	NaN	NaN	1	NaN
ceiling_height_agl:m	28.381035	NaN	NaN	1	NaN
total_cloud_cover:p	24.800315	NaN	NaN	1	NaN
diffuse_rad_1h:J	24.181032	NaN	NaN	1	NaN
effective_cloud_cover:p	24.060679	NaN	NaN	1	NaN
t_1000hPa:K	23.512646	NaN	NaN	1	NaN
month	20.952290	NaN	NaN	1	NaN
relative_humidity_1000hPa:p	18.112349	NaN	NaN	1	NaN
wind_speed_u_10m:ms	17.232760	NaN	NaN	1	NaN
visibility:m	16.736032	NaN	NaN	1	NaN
dew_point_2m:K	14.606567	NaN	NaN	1	NaN
year	12.644342	NaN	NaN	1	NaN
is_in_shadow:idx	12.145240	NaN	NaN	1	NaN
is_estimated	9.418227	NaN	NaN	1	NaN
wind_speed_v_10m:ms	8.607348	NaN	NaN	1	NaN
is_day:idx	8.116596	NaN	NaN	1	NaN
wind_speed_10m:ms	7.259861	NaN	NaN	1	NaN
msl_pressure:hPa	5.702147	NaN	NaN	1	NaN
precip_type_5min:idx	4.785672	NaN	NaN	1	NaN
absolute_humidity_2m:gm3	4.536224	NaN	NaN	1	NaN
sfc_pressure:hPa	4.351804	NaN	NaN	1	NaN
pressure_50m:hPa	4.132368	NaN	NaN	1	NaN
pressure_100m:hPa	4.102240	NaN	NaN	1	NaN
air_density_2m:kgm3	3.756659	NaN	NaN	1	NaN
snow_water:kgm2	3.682171	NaN	NaN	1	NaN
precip_5min:mm	2.170361	NaN	NaN	1	NaN
fresh_snow_24h:cm	1.778663	NaN	NaN	1	NaN
super_cooled_liquid_water:kgm2	1.441840	NaN	NaN	1	NaN
estimated_diff_hours	1.312156	NaN	NaN	1	NaN
rain_water:kgm2	1.181463	NaN	NaN	1	NaN
fresh_snow_12h:cm	0.863525	NaN	NaN	1	NaN

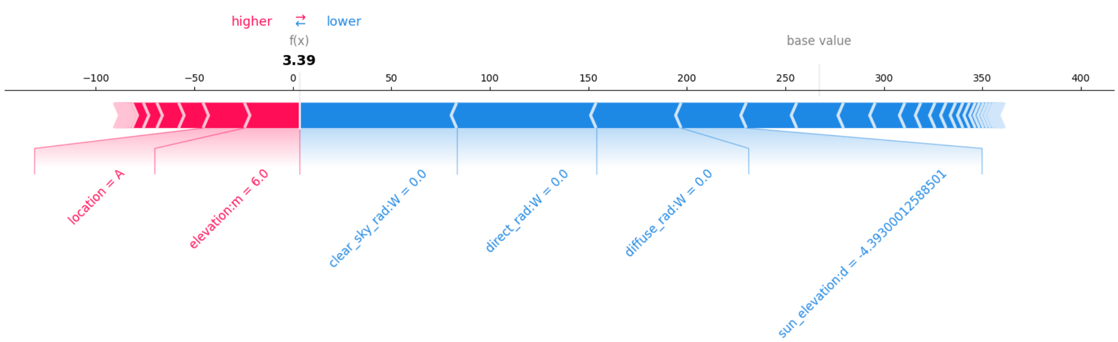
prob_rime:p	0.033327	NaN	NaN	1	NaN
dew_or_rime:idx	0.030201	NaN	NaN	1	NaN
fresh_snow_1h:cm	0.026387	NaN	NaN	1	NaN
snow_melt_10min:mm	0.011094	NaN	NaN	1	NaN
fresh_snow_6h:cm	0.009304	NaN	NaN	1	NaN
elevation:m	0.005508	NaN	NaN	1	NaN
wind_speed_w_1000hPa:ms	0.000008	NaN	NaN	1	NaN
location	0.000000	NaN	NaN	1	NaN
fresh_snow_3h:cm	-0.002899	NaN	NaN	1	NaN
snow_depth:cm	-0.040388	NaN	NaN	1	NaN

	p99_low
direct_rad:W	NaN
clear_sky_rad:W	NaN
diffuse_rad:W	NaN
sun_elevation:d	NaN
clear_sky_energy_1h:J	NaN
hour	NaN
sun_azimuth:d	NaN
cloud_base_agl:m	NaN
weekday	NaN
direct_rad_1h:J	NaN
ceiling_height_agl:m	NaN
total_cloud_cover:p	NaN
diffuse_rad_1h:J	NaN
effective_cloud_cover:p	NaN
t_1000hPa:K	NaN
month	NaN
relative_humidity_1000hPa:p	NaN
wind_speed_u_10m:ms	NaN
visibility:m	NaN
dew_point_2m:K	NaN
year	NaN
is_in_shadow:idx	NaN
is_estimated	NaN
wind_speed_v_10m:ms	NaN
is_day:idx	NaN
wind_speed_10m:ms	NaN
msl_pressure:hPa	NaN
precip_type_5min:idx	NaN
absolute_humidity_2m:gm3	NaN
sfc_pressure:hPa	NaN
pressure_50m:hPa	NaN
pressure_100m:hPa	NaN
air_density_2m:kgm3	NaN
snow_water:kgm2	NaN
precip_5min:mm	NaN

```
fresh_snow_24h:cm                   NaN
super_cooled_liquid_water:kgm2      NaN
estimated_diff_hours                NaN
rain_water:kgm2                     NaN
fresh_snow_12h:cm                   NaN
prob_rime:p                         NaN
dew_or_rime:idx                     NaN
fresh_snow_1h:cm                    NaN
snow_melt_10min:mm                  NaN
fresh_snow_6h:cm                    NaN
elevation:m                         NaN
wind_speed_w_1000hPa:ms             NaN
location                            NaN
fresh_snow_3h:cm                    NaN
snow_depth:cm                       NaN
```

[ ]:
```
#auto.explain_rows(train_data=X_train, model=predictor, plot="force",
↪rows=X_train[:1])
```





[ ]:

```
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_all.ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_all.ipynb to pdf
[NbConvertApp] Support files will be in
notebook_pdfs/submission_82_jorge_with_feature_importance_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_82_jorge_with_feature_importance_files/notebook_pdfs
[NbConvertApp] Writing 121656 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 2064363 bytes to
notebook_pdfs/submission_82_jorge_with_feature_importance.pdf
```

```
[ ]: CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_82_jorge_with_feature_importance.pdf',
'autogluon_all.ipynb'], returncode=0)
```